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ABSTRACT

The 10th Federal Forecasters Conference provided a forum where 127 forecasters from different federal agencies and other organizations met to discuss various aspects of the conference's theme, "Forecasting in the New Millennium," that could be applied in the United States. A keynote address, "Procedures for Auditing Federal Forecasts" by J. Scott Armstrong, was followed by a panel presentation to set the stage for 2 concurrent sessions at which 24 papers were presented. These papers, or in some cases abstracts, are grouped into topics of: (1) "The North American Industry Classification System"; (2) "Economic Forecasting Issues"; (3) "Budget Forecasting for the Food Stamp Program"; (4) "New Developments in Health Manpower Forecasting"; (5) "Forecasting Agricultural Commodity Prices"; (6) "Y2K Forecasts from Denial to Doomsday"; (6) "Economic Forecasting Issues: Population and Labor Force"; (7) "Forecasting Techniques"; (8) "Compendium of Techniques"; and (9) "Forecasting the Food Component of the Consumer Price Index." Nine papers from the International Symposium on Forecasting are also included. Of these, "The National Center for Education Statistics Projections Program" by Debra E. Gerald has the most relevance for educators. Each paper contains references. (Contains 60 tables and 65 figures.) (SLD)

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TM

The 10th Federal Forecasters Conference - 1999

Papers and Proceedings

Bureau of Labor Statistics
Washington, DC
June 24, 1999

Cosponsored by

Bureau of the Census
Bureau of Economic Analysis
Bureau of Health Professions
Bureau of Labor Statistics
Department of Veterans Affairs
Economic Research Service
Immigration and Naturalization Service
National Center for Education Statistics
U.S. Geological Survey

and

Selected Papers

19th International Symposium on Forecasting
Capitol Hilton Hotel
Washington, DC
June 27-30, 1999

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Announcement

The 11th
Federal Forecasters Conference
(FFC/2000)

will be held

on

September 14, 2000

in

Washington, DC

More information will be available in the coming months.

The 10th Federal Forecasters Conference - 1999

Papers and Proceedings

and

Selected Papers

19th International Symposium on Forecasting

Edited by
Debra E. Gerald
National Center for Education Statistics

U.S. Department of Education
Office of Educational Research and Improvement

The 10th
Federal Forecasters Conference

Papers and Proceedings

Bureau of Labor Statistics
Washington, DC
June 24, 1999

Federal Forecasters Conference Organizing Committee

Stuart Bernstein
Bureau of Health Professions
U. S. Department of Health and Human Services

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Bureau of Labor Statistics
U.S. Department of Labor

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Bureau of Economic Analysis
U.S. Department of Commerce

Peg Young
Immigration and Naturalization Service
U.S. Department of Justice

Federal Forecasters Conference Organizing Committee

(Left to right) **Norman C. Saunders**, Bureau of Labor Statistics; **Stuart Bernstein**, Bureau of Health Professions; **Debra E. Gerald**, National Center for Education Statistics; **Karen S. Hamrick**, Economic Research Service; **Howard N Fullerton, Jr.**, Bureau of Labor Statistics; **Jeffrey Osmint**, U.S. Geological Survey; and **Kathleen Sorensen**, Department of Veterans Affairs. (Not Pictured): **Stephen A. MacDonald**, Economic Research Service; **Tammany J. Mulder**, Bureau of the Census; **Clifford Woodruff**, Bureau of Economic Analysis; and **Peg Young**, Immigration and Naturalization Service.

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Foreword

In the tradition of past meetings of federal forecasters, the 10th Federal Forecasters Conference (FFC/99) held on June 24, 1999, in Washington, DC, provided a forum where forecasters from different federal agencies and other organizations could meet and discuss various aspects of forecasting in the United States. The theme was "Forecasting In the New Millennium."

One hundred and seventy-seven forecasters attended the day-long conference. The program included opening remarks by Debra E. Gerald and welcoming remarks from Neal Rosenthal, Associate Commissioner of the Office of Employment Projections, Bureau of Labor Statistics. Professor J. Scott Armstrong of the Wharton School, University of Pennsylvania delivered the keynote address. The address was followed by a panel presentation given by Anne B. W. Effland, historian/social science analyst, of the Economic Research Service, U.S. Department of Agriculture, Calvin Beads, Jr., computer specialist, of the U.S. Department of Veterans Affairs, and Robert W. Tinney, economist, of the Office of the Secretary of Defense, Department of Defense. Stuart Bernstein of the Bureau of Health Professions and Stephen A. MacDonald of the Economic Research Service presented awards from the 1999 Federal Forecasters Forecasting Contest. Jeffrey Osmint of the U.S. Geological Survey presented awards for Best Papers from FFC/97.

In the afternoon, ten concurrent sessions in two time slots were held featuring three panels and 20 papers presented by forecasters from the Federal Government, private sector, and academia. A variety of papers were presented dealing with topics related to agriculture, budget, the economy, health, labor, population, and forecasting techniques. These papers are included in these proceedings. Another product of the FFC/99 is the *Federal Forecasters Directory 1999*.

In addition, selected papers from federal presenters at the 19th International Symposium on Forecasting (ISF '99), held in Washington, DC from June 27-30, 1999, are also included in these proceedings. This symposium was sponsored by the International Institute of Forecasters under the direction of Peg Young, general chairperson, and Karen S. Hamrick, program chair.

Acknowledgments

Many individuals contributed to the success of the 10th Federal Forecasters Conference (FFC/99). First and foremost, without the support of the cosponsoring agencies and dedication of the Federal Forecasters Conference Organizing Committee, FFC/99 would not have been possible. Debra E. Gerald of the National Center for Education Statistics (NCES) served as chairperson and developed conference materials. Peg Young of the Immigration and Naturalization Service, Debra Gerald of NCES, Karen Hamrick of the Economic Research Service (ERS), and Kathleen Sorensen of the U.S. Department of Veterans Affairs were instrumental in arranging for the keynote speaker and panelists for the morning session. Norman Saunders prepared the announcement and call for papers and provided conference materials. In addition, Norman Saunders served as the photographer for the day-long conference. Stuart Bernstein of Bureau of Health Professions organized and conducted the Federal Forecasters Forecasting Contest. In addition to organizing the Federal Forecasters Forecasting Contest, Stephen M. MacDonald of ERS provided conference materials. Karen S. Hamrick of ERS served as program chair and organized the afternoon concurrent sessions. Tammany J. Mulder and Laura Heaton of the Bureau of the Census arranged for financial support of the conference. Jeffrey Osmint of U.S. Geological Survey provided conference materials and produced special awards for the forecasting contest and certificates of appreciation. Kathleen Sorensen of the U.S. Department of Veterans Affairs provided conference materials. Howard N Fullerton, Jr. of the Bureau of Labor Statistics secured conference facilities and handled logistics. Peg Young of the Department of Veterans Affairs provided conference materials.

Also, recognition goes to Clifford Woodruff of the Bureau of Economic Analysis for his support of the Federal Forecasters Conference.

A special appreciation goes to Peg Young and the International Institute of Forecasters for their support of this year's conference.

A deep appreciation goes to Neale Baxter, a retiree from the Bureau of Labor Statistics, for reviewing the papers presented at the Ninth Federal Forecasters Conference and selecting awards for the FFC/97 Best Conference Papers.

Many thanks go to Linda D. Felton and Patricia A. Saunders of the Economic Research Service, U.S. Department of Agriculture for directing the organization of conference materials into packets and staffing the registration desk. Certificates of Appreciation were presented to Linda Diane Felton and Patricia Saunders for their outstanding work on the conference over a number of years and making sure that the conferences ran smoothly.

Last, special thanks go to all presenters, discussants, and attendees whose participation made FFC/99 a very successful conference.

1999 Federal Forecasters Forecasting Contest

WINNER

John Golmant
Administrative Office of the United States Courts

HONORABLE MENTION

Terry Schau, Bureau of Labor Statistics
W. Vance Grant, National Library of Education
Peggy Podolak, U.S. Department of Energy
Tancred Lidderdale, Energy Information Administration
Betty W. Su, Bureau of Labor Statistics
Tim Dowd, Joint Committee on Taxation
Thomas D. Snyder, National Center for Education Statistics
Patrick Walker, Administrative Office of the U. S. Courts
Paul Campbell, Bureau of the Census
Mirko Novakovic, Bureau of Labor Statistics

CONSISTENTLY ACCURATE FORECASTS

Thomas D. Snyder, National Center for Education Statistics
Betty W. Su, Bureau of Labor Statistics

International Symposium on Forecasting—1999

Winner

Charles K. ReCorr, Merrill Lynch Private Client Group

Honorable Mention

John Golmant, Administrative Office of the U. S. Courts
Michele Hibon, INSEAD, Fontainbleau, France

Contest Answers

Dow-Jones Industrial Average **10596**
Japanese Yen per U.S. Dollar **120.56**
Closing Spot Price for Gold **$268.20**
High Temperature in Paris, France **80° F**
Most Home Runs Hit by a Major League Baseball Player **20**

1997 Best Conference Paper

WINNER

"An Annual Model for Forecasting Corn Prices"

Paul C. Westcott
Economic Research Service

HONORABLE MENTION

"Revising the Producer Prices Paid by Farmers Forecasting System"

David Torgerson
Economic Research Service

John Jinkins
Economic Research Service

"Projections of Elementary and Secondary Public Education Expenditures by State"

William J. Hussar
National Center for Education Statistics

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The 10th
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Scenes from the Conference

Photos by Norman Saunders, Bureau of Labor Statistics

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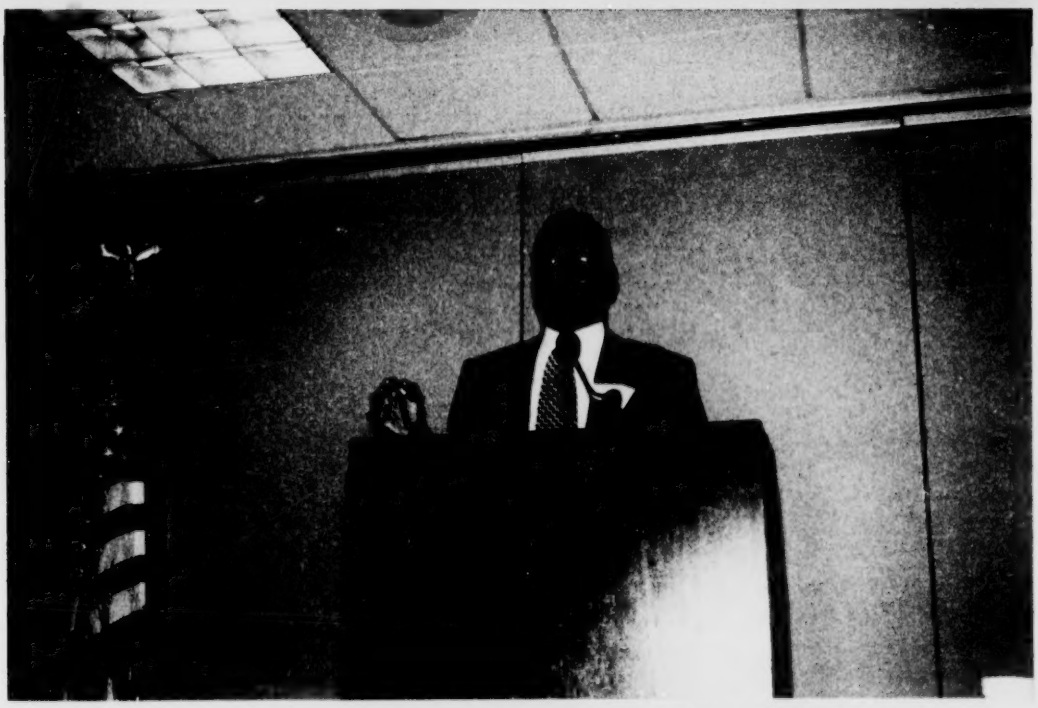
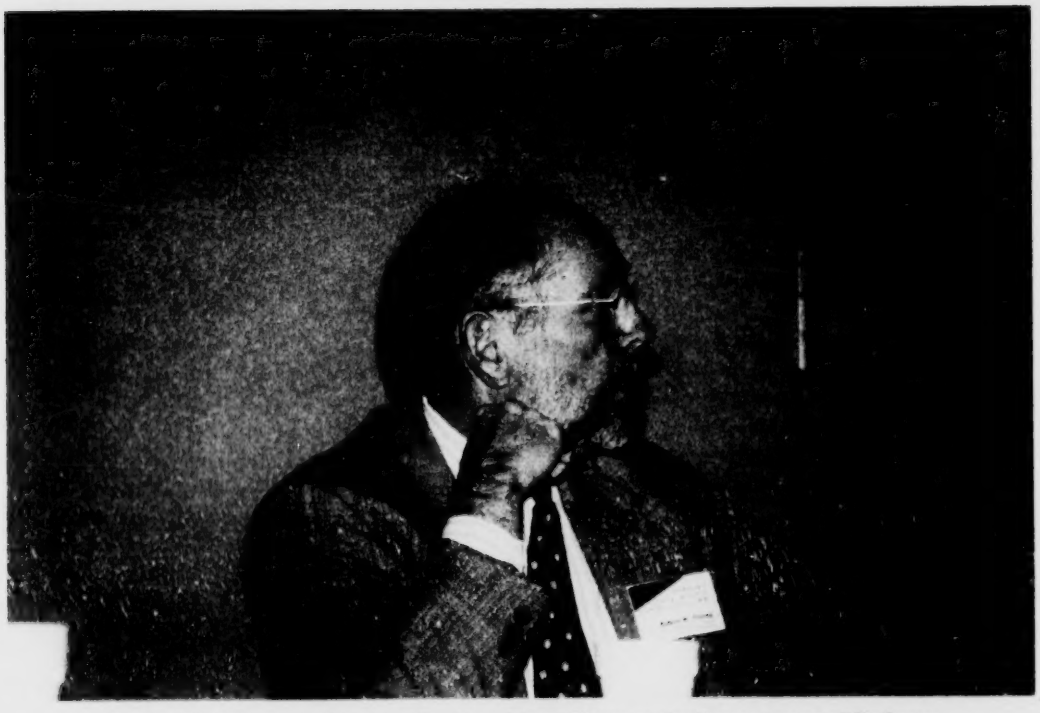
J. Scott Armstrong explains the procedures for auditing federal forecasts.

Anne B. W. Effland looks back at forecasting at USDA.



Calvin Beads, Jr. charts a course for forecasting at VA.



Robert W. Tinney reflects on the recruiting efforts at the Department of Defense.

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Award Winners from FFC/99.

Linda D. Felton and Patricia prepare the FFC registration table.

Message from the Chairperson

Debra E. Gerald
National Center for Education Statistics
U.S. Department of Education

The Federal Forecasters Conference is a collaborative effort of forecasters from various federal agencies in the United States Government. The conference provides a forum in which forecasters from many disciplines can share information on data issues, forecasting techniques, and forecast evaluation.

This year, the Federal Forecasters Conference celebrated its 10th anniversary meeting. The first conference was held in 1988. At that conference, 50 federal forecasters from 20 different agencies attended the day-long event. Over the years, the conference has grown in the number of attendees and agency participation. We are very thankful to you for having supported the conference over the years. Many of you have returned year after year. This year, more than 220 individuals from 60 public and private organizations registered for the conference. This growth is due to the efforts of the organizing committees and the support of their sponsoring agencies.

The members of the organizing committee for the 10th Federal Forecasters Conference are Stuart Bernstein, Bureau of Health Professions; Howard N Fullerton, Jr., Bureau of Labor Statistics; Karen S. Hamrick, Economic Research Service; Stephen A. MacDonald, Economic Research Service; Tammany J. Mulder, Bureau of the Census; Jeffrey Osmint, U.S. Geological Survey; Norman C. Saunders, Bureau of Labor Statistics; Kathleen Sorensen, Department of Veterans Affairs; Clifford Woodruff III, Bureau of Economic Analysis; and Peg Young, Immigration and Naturalization Service.

In addition to serving on the organizing committee of the this year's conference, three of the committee members made up the organizing committee for the International Symposium on Forecasting which was held from June 27-30, 1999 in Washington, DC. Peg Young served as general chairperson. As program chair, Karen S. Hamrick organized the sessions. Stephen A. MacDonald was publicity chairperson.

We are especially pleased to have J. Scott Armstrong from The Wharton School, University of Pennsylvania as our keynote speaker for the 10th anniversary meeting of the Federal Forecasters Conference. Professor Armstrong also has the distinction of being the feature presenter at the first Federal Forecasters Conference in 1988. He has a long and distinguished career in forecasting and concentrates in the area of forecasting methods.

We are also indebted to those who provided support for the conferences during the early and mid-1990s. In the conference issue of *The Federal Forecasters* newsletter are listed the past cosponsoring agencies and past organizing committee members. Excerpts from the newsletter follow and recognize those individuals and organizations for their contributions to past Federal Forecasters Conferences. Their collaborative efforts have made The Federal Forecasters Conference a resounding success over the years.

The National Center for Education Statistics sponsored the first two conferences (1988 and 1989). With support from other agencies, lead agencies that organized the early meetings were Economic Research Service (1990), Bureau of Labor Statistics (1991), Bureau of Economic Analysis (1992), and Energy Information Administration (1993 and 1994). In lieu of a conference, a *Federal Forecasters Directory* was published in 1995. The 1996 and 1997 conferences were organized through a joint effort of cosponsoring agencies. In lieu of a conference in 1998, a *Federal Forecasters Directory* was published.

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Founding and Cosponsoring Agencies

We are profoundly indebted to the founding agencies which have served as the initial sponsors of the Federal Forecasters Conference and sustained by the core of nine cosponsoring agencies whose dedicated members of the organizing committee continue to support and maintain a network for federal forecasters across a variety of disciplines.

Currently, there are nine federal agencies:

Bureau of the Census, U.S. Department of Commerce
Bureau of Economic Analysis (BEA), U.S. Department of Commerce
Bureau of Health Professions (BPHr), U.S. Department of Health and Human Services
Bureau of Labor Statistics (BLS), U.S. Department of Labor
Department of Veterans Affairs (VA)
Economic Research Service (ERS), U.S. Department of Agriculture
Immigration and Naturalization Service (INS), Department of Justice
National Center for Education Statistics (NCES), U.S. Department of Education
U.S. Geological Survey (USGS), Department of the Interior

Past cosponsoring agencies have been:

Central Intelligence Agency (CIA)
Energy Information Administration, U.S. Department of Energy
Environmental Protection Agency (EPA)
Health Care Financing Administration (HCFA)
(former) Bureau of the Mines
(former) Office of Technology Assessment

People

The continued success of the Federal Forecasters Conference would not be possible without the dedication and unwavering commitment of current and past members of the organizing committee.

The current team members are:

Debra E. Gerald, NCES (1988, 1989 cochair, 1990, 1991, 1992, 1993, 1994, 1995, 1996 chair, 1997 chair, 1998, 1999 chair)
Stuart Bernstein, BHPr (1989, 1990, 1994, 1995, 1996, 1997, 1998, 1999)
Karen S. Hamrick, ERS (1990 cochair, 1991, 1992, 1993, 1994, 1995, 1996, 1997, 1998, 1999)
Howard N Fullerton, Jr., BLS (1991 cochair, 1992, 1993, 1994, 1995, 1996, 1997, 1998, 1999)
Norman C. Saunders, BLS (1991 cochair, 1992, 1994, 1995, 1996, 1997, 1998, 1999)
Stephen A. MacDonald, ERS (1993, 1994, 1995, 1996, 1997, 1998, 1999)
Peg Young, INS (1993, 1994, 1995, 1996, 1997, 1998, 1999)
Jeffrey Osmint, USGS (1996, 1997, 1998, 1999)
Clifford Woodruff III, BEA (1997, 1998, 1999)
Kathleen Sorensen, VA (1998, 1999)
Tammany J. Mulder, Bureau of the Census (1999)

Past members have included the following individuals:

Paul J. Horn, NCES (1989)
Kenneth Johnson, BEA (1989)
William C. Sonnenberg, NCES (1988 chair, 1989 cochair)
Naomi Verdugo, Army (1989)
Ralph M. Monaco, ERS (1989, 1990 cochair)
Paul Campbell, Bureau of the Census (1990, 1991, 1992, 1993, 1995, 1996, 1997)
William J. Hussar, NCES (1989, 1990)
Herbert Traxler, BHPr (1990, 1991, 1992)
Methodology Center, CIA (1990, 1991, 1992, 1993)
Zoe Ambargis, BEA (1991, 1993, 1995, 1996)
Peter Blair, former Office of Technology Assessment (1991)
John Kort, BEA (1991)
Walter A. Rosenbaum, EPA (1991)
Thomas Lienesch, BEA (1992, chair, 1993)
Patricia Devine, former Bureau of Mines (1992)
Ronald Earley, EIA (1992, 1993 chair, 1995, 1996)
Douglas Maxwell, ERS (1992)
Mai Nguyen, Research and Development, CIA (1992)
David Rejeski, EPA (1992, 1993)
Ethan Smith, USGS (1992, 1993, 1995, 1996)
Sandra Absalom , former Bureau of Mines (1993)
Ching Yu, former Bureau of Mines (1993)
Joe Abe, EPA (1993)
David Costello, EIA (1994 chair, 1995, 1996)
Michael Colby, EPA (1995)
Ching Yu, USGS (1995)
Andy Bernat, BEA (1996)
Gabriella Lombardi, EPA (1996)
John H. Phelps, HCFA (1997, 1998)
Laura Heaton, Bureau of the Census (1998, 1999)

Publications

These products include the *Federal Forecaster Directory*, published in 1988, 1989, 1990, 1991, 1992, 1995, 1996, 1997, 1998, and 1999, and *Federal Forecasters Conference: Papers and Proceedings*, published for these conferences in 1988, 1989, 1990, 1991, 1992, 1993, 1994, 1996, 1997 and 1999.

Keynote Address

Procedures for Auditing Federal Forecasts

J. Scott Armstrong
The Wharton School, University of Pennsylvania

I, along with over 40 leading researchers, have been developing principles based on prior research on forecasting. The principles describe which procedures to use under what conditions. Comparative empirical studies have been particularly useful in this effort. To ensure that the principles cover all situations, we have also drawn upon expert opinion.

Over 130 principles have been developed for forecasting. These should help to:

* structure the problem,
* obtain and prepare relevant information,
* apply forecasting methods,
* evaluate methods, and
* use forecasts effectively.

Use of the forecasting principles can help to avoid liability by showing that attempts were made to follow best practice. In addition, the principles should lead to more accurate forecasts, improved assessments of uncertainty, improved use of forecasts, and/or reduced costs of forecasting.

The principles are needed for important forecasts, especially for situations where opinions differ and emotions are high. For example, what are the predicted effects of a voucher plan for schools, charges for the amount of garbage produced by households, reduction of welfare benefits, privatizing mass transportation, reducing the capital gains tax, legalizing drugs, use of the death penalty, reducing the minimum wage, deregulating businesses, reducing tariffs, or passage of nondiscretionary concealed handgun laws? These represent only a few of the many topics where formal approaches have led to forecasts that conflict with commonly-held views.

The principles are used to select and apply forecasting methods. So I will briefly describe the ten major approaches to forecasting: (1) expert forecasting; (2) judgmental bootstrapping; (3) conjoint analysis; (4) intentions; (5) role-playing; (6) analogies; (7) expert systems; (8) rule-based forecasting; (9) extrapolation; and (10) econometric methods.

While most of the principles are not controversial, many are often unwittingly violated in practice.

Examples include:

* use structured methods
* combine forecasts from at least five sources
* provide prediction intervals
* obtain forecasts from a heterogeneous group of experts
* match the forecasting method to the situation
* provide forecasts for alternative interventions
* be conservative when there is uncertainty
* use domain knowledge when making forecasts.

Some principles conflict with received wisdom. Here are some examples:

* use quantitative rather than qualitative methods when large changes are involved
* do not use statistical criteria for selecting forecasting methods (do not use R-square)
* use theory for model development (once accepted, but currently out of favor).

As might be expected, the principles (including those on the previous page) are generally dependent upon the conditions involved in the situation.

In some cases the principles are based on little evidence. In other cases, however, empirical evidence is extensive. Two well-established findings that conflict with received wisdom are:

*use simple methods unless there is strong evidence that complexity is needed
* do not revise quantitative forecasts.

The principles are provided as a checklist so they can be used to audit an agency's forecasting procedures. It is recommended that the ratings be made independently by three to five unbiased experts.

The principles are likely to lead to substantial changes in practice. For example, judgmental bootstrapping should be used instead of judgement when repetitive forecasts are involved and when one has no historical data on the dependent variable. Another example involves making forecasts where groups are in conflict: use role-playing rather than expert judgment.

Panel

Federal Forecasting in the New Millennium

When the 20th Century Was the Future: USDA's "New" Outlook Program and the "Future" of Public Forecasting

Anne B. W. Effland
Historian/Social Science Analyst
Economic Research Service
U.S. Department of Agriculture

Technical Improvements to Our Veteran Estimates and Projections Model

Calvin Beads, Jr.
Computer Specialist
Office of Planning and Analysis
U.S. Department of Veterans Affairs

Forecasting and Analysis of Military Recruiting Plans and Programs

Robert W. Tinney
Economist
Directorate for Accession Policy
Office of the Secretary of Defense
Department of Defense

Representing three federal agencies, the panel examined federal forecasting in this era of rapid change and how these changes will affect their work in the new millennium. Anne B. W. Effland set the stage by examining the ways in which forecasters in the U.S. Department of Agriculture faced these questions in the early years of this century. Calvin Beads, Jr. and Robert W. Tinney spoke of what changes must be made to continue to provide relevant and reliable forecasts in the new millennium and what changes will be thrust upon us by the new ways of doing our work due to changes in technology.

"WHEN THE 20TH CENTURY WAS THE FUTURE: USDA'S 'NEW' OUTLOOK PROGRAM AND THE 'FUTURE' OF PUBLIC FORECASTING"

Anne B. W. Effland
Economic Research Service, USDA

Introduction

> "The vital need of today is a clear and searching glance into the future, a forecast of crop results which shall fairly indicate them in advance." (USDA 1889, 201)

So wrote Jacob Richards Dodge, Chief Statistician of the U.S. Department of Agriculture, in the Annual Report of the Secretary in 1889. As crop surpluses weighed on prices, and populists weighed on government to regulate the financial and transportation interests they identified as responsible, Dodge envisioned a day when accurate, systematic collection of agricultural statistics might support a crop forecasting program that would allow farmers to make informed planting decisions and avoid producing beyond the demand for their product. Twenty-three years later, in 1912, the Department provided its first quantitative yield and production forecasts, and in 1923, it began its outlook program with the first annual outlook conference.

To provide some historical perspective on the theme of this conference, "Forecasting in the New Millennium," this paper examines the development of USDA's outlook program in the latter years of the 19th century and the early years of the 20th. It inquires into the process by which a past group of statisticians and economists arrived at a forecasting program for their times, in hopes of informing and inspiring similar reflections as we enter our own future.

On some levels, both periods have much in common. Like the end of our own century, the end of the last century witnessed, to paraphrase the call for papers for this conference, changing ideas about government and its role in the daily lives of citizens (government regulation of railroads and interstate commerce had recently been established, for example), new ways of doing business (catalog sales, national chains, and commercial advertising created a national consumer culture), new ways of organizing corporations (holding companies and corporations provided new avenues for growth and expansion), new ways of communicating (the telephone made long distance voice communication instantaneous), and new conceptions of employment and career (huge industrial plants led to growing specialization of jobs and fed the rise of unions, while new office jobs and positions for professional and technical experts created a new "middle" class of workers). The Industrial Revolution (like the current Information Revolution) was here, and many were "straining to keep up in an era of change almost too rapid to comprehend."

Just as the current version of these events leads us to consider directions for the future in the 21st century, so the events at the turn of the last century led many to think about changes that would improve their own futures in the 20th century. The development of USDA's forecasting program offers an opportunity to examine how forward-looking leaders of the agricultural economy built a program they believed would address the long-term, recurrent problems of agriculture, particularly surpluses and the low prices that accompanied them. They adopted a systematic approach that integrated aspects of programs already underway with new ideas arising from the rapid economic and social change them. With deliberate purpose, professionals like J. R. Dodge worked to educate farmers, businessmen, and politicians about the value of government-provided economic information, which could help stabilize agricultural production and prices based on market principles.

Deriving their convictions from the context of their own times--the problems before them and the economic theories explaining them--these leaders established a program of reliable and scientifically sound public forecasts that has lasted through the century and that continues to inform decisionmakers, although not always in ways imagined by its originators. The story of establishing the agricultural outlook program illustrates how a cohort of dedicated professionals envisioned public solutions to the problems of their day in such a way that those solutions became the basis for solutions to future problems they could not anticipate. The experiences of these leaders who came before may offer useful insights as this conference contemplates similar kinds of questions for the next century, and even millennium.

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USDA's forecasting program in the 1920s was the culmination of public support in three critical areas: long-term collection of reliable agricultural statistics, newly developed research into accurate methodologies for forecasting, and a system to distribute and interpret the national-level forecasting work to individual farmers. This presentation describes each of these developments individually, examining the role each played in the establishment of the Department's outlook program in 1923 and their roles in the continuing influence of the outlook program through the remainder of the 20th century and to the brink of the new millennium.

Developing the Collection of Agricultural Statistics

The Department of Agriculture had a well-developed program for collecting statistics on agriculture by the end of the 19th century. In response to requests from Eastern farmers, who had begun to feel the pressure of new supplies of wheat and other staples from the expanding West, collection of agricultural statistics through voluntary reporting by farmers and other interested parties began with an appropriation to the U.S. Patent Office in 1839, as well as the inclusion of agricultural questions in the 1840 census. Despite inconsistent appropriations from Congress, Commissioner of Patents Henry Ellsworth followed his own convictions, and his property interests in newly settled western lands, and continued collection and reporting of crop statistics until his resignation in 1845. His successors in the Patent Office did not share his commitment to agricultural statistics, but annual crop reports continued until the establishment of the Department of Agriculture in 1862, when monthly crop reports began in the new Department (Ebling 1939, USDA 1969).

Great expectations for the value of crop reports accompanied USDA's early program. Wrote Commissioner of Agriculture Isaac Newton in 1863, "Too much cannot be said in favor of agricultural statistics. They hold . . . the chart which is to reveal to the husbandman and the merchant the great laws of supply and demand--of tillage and barter--thus enabling both to work out a safe and healthy prosperity" (Ebling 1939, 727). Crop estimates did provide useful information to farmers about available supplies, putting them on the same footing with buyers as they marketed their crops, but the estimates did not provide information early enough in the season to help farmers adjust their production levels to meet anticipated demand. The opening of new lands in the West and a series of good crops in Europe had created excess supplies, especially of wheat, and brought disastrously low prices. Without a method for providing farmers with information on how much others were going to plant, surpluses could not be anticipated by individuals.

Information on expected production, however, at least offered producers a chance to affect how and when they marketed their crops. Repeated economic downturns and depressions in the agricultural sector from the end of the Civil War in 1865 to the end of the 19th century emphasized the importance of informed marketing for farmers, so they might choose the best moment to sell in order to receive the highest price. But crop statistics, it turned out, also had the power to influence the market directly, a power made clear at the result of scandal. In 1905, a senior member of USDA's Bureau of Statistics was found to have manipulated information on cotton acreage and even to have leaked production estimates to speculators in New York, providing them the opportunity to reap artificially high profits in the cotton trade (Ebling 1939; Taylor and Taylor 1952).

Following the scandal, the founding of the Crop Reporting Board in 1905 established a system that continues today, in which a group of senior experts in the Bureau of Statistics make final crop estimates under secure conditions. The new system enhanced public confidence in the accuracy and integrity of USDA's monthly crop reports. At the same time, a Presidential commission investigating the agricultural statistics program, following the 1905 scandal and a controversy between USDA and the Census Bureau over discrepancies in estimates of acreage planted for 1900, raised anew the idea of a forecasting program in the Department. Their investigation of the scandal revealed a distinct advantage held by the large trading firms: they could hire analysts to take USDA's statistical reports and turn them into estimates of future production (Taylor and Taylor 1952).

The commission recommended in 1906 that the Department make use of its expertise and collected statistics to predict production levels before harvest so farmers would have the same information as traders for making marketing decisions. By 1912, the first quantitative forecast of yield and total production appeared, calculated using the "par" method that related planted acreage and current condition of crops to the average yield under average conditions. Statisticians referred to the results as "production indications," rather than forecasts, but farmers and other using the Department's monthly reports considered them production forecasts (Taylor and Taylor 1952; USDA 1969).

Developing New Methodologies

Although these pre-harvest production forecasts allowed farmers to make more timely marketing decisions, they came too late to affect farmers' planting decisions. They could help farmers get the best price, but they could not help prevent surpluses. Forecasts early enough to affect planting decisions awaited the emergency needs of wartime. In 1917, when army officials asked the Bureau for a prediction of the probable spring wheat crop, Bureau Chief Leon Estabrook oversaw a survey of wheat farmers' planting intentions, the results of which were provided to the army for planning purposes. Comparison of the spring survey results with actual harvest numbers revealed a close match. Intentions-to-plant surveys, and soon after similar surveys of livestock farmers' intentions to breed hogs and cattle, became a powerful new tool for forecasting production early enough to allow farmers to make planting breeding decisions. Estabrook later reported the development of forecasting based on the planting intentions of farmers as "among the more novel" accomplishments of the Bureau of Crop Estimates (Ebling 1939; Estabrook 1920).

By 1922, when the Bureau of Crop Estimates, formerly the Bureau of Statistics, was joined with the Bureau of Markets as the Bureau of Agricultural Economics (BAE), the discipline of agricultural economics had become a dynamic field of applied economics, energized by the disturbing depression in agriculture that followed the end of World War I. While the rest of the country's economy enjoyed great prosperity in the 1920s, the farm economy suffered from rapidly falling prices and expanding supplies. Largely the result of post-war disruptions of wartime demand for agricultural products in Europe, the economic distress spurred much research and attention to methods for helping farmers make better production and marketing decisions.

Supported by these growing concerns about the future of agriculture, and concurrent with the development of surveys that provided information to statisticians and economists early enough to support pre-planting forecasts of production, BAE economists were developing new quantitative methods to use the Department's accumulated historical statistics (Hamilton 1999). By identifying statistical relationships among the data, the economists hoped to more accurately use annual data on farmers' planting and breeding intentions to forecast annual production levels.

But forecasting production levels only offered farmers an a idea of what crops might be in relative surplus in the upcoming year. Many pointed out the need to provide farmers with some idea of what the returns for planting different crops might be. For that farmers needed price forecasts. Critical research in applied methodologies by the BAE staff during the 1920s eventually led to the development of reliable price forecasting capabilities. Bureau economists published both academic and popular explanations of their new methods, from articles on a variety of statistical correlation methods in the *Journal of the American Statistical Association* (Tolley and Ezekiel 1923; Ezekiel 1924; Bean 1930) to such BAE bulletins as "What Makes the Price of Oats?," "Factors Affecting the Price of Hogs," and "Factors Affecting the Price of Cotton" (Killough 1925; Ezekiel and Haas 1926; Smith 1928).

Developing a Dissemination Program

As the agricultural depression of the 1920s dragged on, pressure from farm organizations and other agricultural interests mounted for a national policy of price support for farm products through underwriting of exports. Agricultural economists generally opposed such a program and instead advocated better information to improve production and marketing decisions by farmers. As USDA's annual report noted in 1923, "The practical purpose of the price-analysis work is to give the farmer the benefit of a scientific analysis of his problem, so that he may be able to make the best estimate possible with the facts available" (USDA 1923). The BAE's periodic crop reports and production, yield, and price forecasts formed part of this approach, but leaders in the agency and within the new profession of agricultural economics wished to offer farmers a more timely and comprehensive guide for their production and marketing decisions.

Building on the well-developed program for collecting agricultural statistics and on newly developed quantitative methods for using those statistics to forecast production and price trends, economists in the BAE, led by Henry C. Taylor, the new Bureau's chief, began an ambitious program of producing an annual outlook for agricultural production and prices to provide farmers and other agricultural interests with the outlook on production and demand for major commodities in the upcoming year (USDA 1920; Tolley 1931; USDA 1942; Taylor and Taylor 1952; Hamilton 1998, 1999). At the time of the initial outlook conference in 1923, Taylor had made clear his views that "the purpose of agricultural forecasting is the wise guidance of production in order that there may continue to be a proper balance

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between the various lines of production and between agriculture and other industries. . . . From the individual point of view, forecasting is the basis of wise farm management and marketing. From the national point of view it is the basis of a national agricultural policy" (Taylor, 1923,).

Taylor's views of agricultural forecasting's value to national policy were expansive and focused on the long-term. He advocated studies of long-term trends in agricultural production and prices "to provide an intelligent basis for determining state and national policies with respect to immigration, foreign trade in farm products, forestry, reclamation and land settlement, and the wise utilization and administration of the remaining public domain" (Taylor 1925, 485) But he reiterated his commitment to providing information, rather than intervention, in a later description of the philosophy behind the outlook program, at a time when policy had taken a more interventionist turn: "Our proposal was not to formulate an agricultural program but to draw a picture of the conditions with respect to the probable supply and demand throughout the competing area. . . .The farmers were not to be told what to do but given the facts they needed in order to act intelligently." (Taylor 1923; USDA 1942, 4-5).

The outlook reports proved popular. By 1930, Secretary of Agriculture Henry Hyde could report that "the agricultural outlook service has now been extended into every state and covers over 40 crops and classes of livestock. This year's outlook report . . . was not only brought directly to more than 200,000 farmers at 4,200 group meetings, but was also used in special and follow-up radio programs which carried the information quickly to several million farmers" (Tolley 1931, 531).

Outlook reports did not remain the same throughout this period, however. Early reports not only provided "the facts," they also came close to telling farmers what to do. For example, in the 1925 outlook report, corn analysts commented "an increased acreage in 1925 does not appear advisable, " while the hog report advised "a further reduction in production is highly undesirable." Dairy analysts found "further expansion in dairying in 1925 seems inadvisable," and wheat analysts warned "growers of hard spring wheat are cautioned not to increase production above domestic requirements." By 1931, analysts provided only their assessments of likely price movements, leaving farmers, or their extension advisors, to derive the appropriate production and marketing decisions from the price information (Tolley 1931, 532).

Between 1923 and 1931, a number of important changes in leadership and organization of the Department had taken place that led to the change in outlook interpretations. Perhaps most importantly, forecasts for lower cotton prices in the fall of 1927 coincided closely with a dramatic drop in the market, suggesting the USDA forecast caused a fall in prices. Influential cotton trading interests took the opportunity to pressure Congress for changes in the forecasting program. Beginning with the Agriculture Appropriations Act in 1929, forecasting of cotton prices was forbidden.

Herbert Hoover, the new President, expanded the proscription to cover all price forecasting. Secretary Hyde's strict interpretation of Hoover's order against price forecasting led to pressure on BAE Chief Nils Olsen to suppress price expectations in the outlook reports. Olsen protested with some success, persuading Hyde to consider the BAE's outlook analysis of prices as the reporting of price trends, rather than the forecasting of prices. But the continued uncertainty of the economy as the world entered the Depression of the 1930s led to a suspension of price forecasting in 1932 anyway, as previously reliable methods no longer produced accurate predictions (Lowitt 1980; Hamilton 1991; Associated Press 1932).

Despite this move away from providing specific advice to farmers about the direction of prices, some in the BAE advocated a greater use of agricultural outlook information to advise farmers and assist them in land use choices that would best match production with demand. The Extension Service had been involved in disseminating outlook reports and adapting them and explaining them to farmers since the beginning of the outlook program, as reflected in Secretary Hyde's enumeration of the 200,000 farmers reached at 4,200 local meetings by the outlook program in 1930. As the BAE slowly reduced the interpretation of its outlook for individual farmers in the national reports, state and county Extension Service staffs became increasingly responsible for interpreting the general information provided by BAE in the light of their local circumstances and the needs of individual farmers. H. R. Tolley, an early director of the outlook work, believed the BAE had "passed the buck" to the states and individual farmers to figure out how to use outlook information (Tolley 1931).

Under Hoover's Federal Farm Board, his program for responding to the growing agricultural crisis, and later as the Roosevelt administration inaugurated the New Deal agricultural programs, outlook work began to serve the needs of agricultural support and planning programs. No longer confident that farmers themselves could turn the agricultural economy around through adjustments to their production and marketing decisions based on reliable information, government programs to control supply and support prices came to rely on crop reports and outlook services for planning acreage reduction and other programs designed to reduce surpluses (Hamilton 1999).

During this period, the BAE's planning function expanded and the agency became the central clearinghouse for agricultural planning in USDA. The agency directed and advised the work of state, county, and community agricultural planning committees, putting forecasting work to the task of national economic planning of food and fiber production through developing individual, local, and regional farm and land use plans (USDA 1942; Baker et al. 1963). Emphasizing intervention over information, the BAE leadership held high expectations that this planning function represented the future of public forecasting in agriculture. Wrote the author of a 1942 report on BAE's outlook work, "Wide fields lie ahead for the further development of . . . outlook information–for outlook work in terms of human needs and of production and marketing to meet those needs–in place of 'supply and demand' as traditionally defined" (USDA 1942).

With the coming of World War II, forecasting the demand for agricultural products and assuring an adequate supply became central to the war effort, as it had in a less developed form during World War I. By the end of the war, however, political patience with Federal economic control of agricultural production planning had worn thin and the BAE was a casualty of the opposition to centralized government planning in the economy. Yet with various Federal commodity support programs firmly in place by the time of this reaction in the late 1940s, and with the established tradition of USDA provision of public information on the agricultural economy, the demand for production and price forecasts for agriculture remained and the outlook program continued in the 1950s without the BAE (USDA 1942; Baker et al. 1963).

Conclusion

For agriculture, three sets of circumstances came together under the distressed economic circumstances of the 1920s and 1930s to support the creation and development of a lasting public forecasting program. Because of the long tradition of supporting government collection of agricultural statistics, a substantial set of historical statistics was available and a system for their continued collection was in place. Because of the prolonged economic distress in the agricultural economy in the late 19th century, and because of the rising interest in applied economic theory brought about by the effects of late 19th century industrialization, research and development of methodologies for improved agricultural economic forecasting found support in the Department and among agricultural leaders and economists outside USDA. And because of efforts to improve farm efficiency and to build parity between rural and urban standards of living in the early 20th century, a field distribution system in the form of the Extension Service was well-established and lent itself to the dissemination of the agricultural outlook program at the local level.

With the three elements joined under the leadership of agricultural economist Henry C. Taylor in the BAE, and with the committed support of Secretary of Agriculture Henry C. Wallace, an impressive public forecasting program was born. Although that powerful partnership changed soon after, with the death of Wallace and the resignation of Taylor, the groundwork laid in the 1920s remained in place and flourished during the severe economic distress of the 1930s. Of course, the agricultural economy has changed much since the 1930s, but the forecasting program has remained and been relied on for information used for an array of public and private purposes since then, including wartime emergencies, commodity programs, and production, storage, trade, and transportation planning.

The intention of this examination of historical events is not to suggest that the beginning of the next century is the same, or even similar, to the beginning of this one, though there are some striking resemblances. It is more to suggest that efforts begun as we entered our current century to take a long-term view and to build a scientifically sound analytical system created the foundation for a program that could respond to changing needs over time. As the context of the nation's agriculture changed over the century, this publicly supported analytical system remained capable of providing the information needed to make economic decisions.

Those looking into the future from 1999, however, might wish to consider whether the foundations of this analytical system that has weathered the 20th century continue to be relevant and sustainable for the 21st century. Will the same three elements--reliable collection of statistics, research into methodologies for improved forecasts, and a system for wide and public dissemination of information--continue to be the appropriate foundations for a valued public forecasting system in the future? And if so, will the traditional public methods of supporting these elements continue to produce the needed results for the next century? These are the kinds of questions that were asked by forward-looking leaders at the beginning of this century and are, in fact, the ones being asked again by many as we enter the next century.

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Technical Improvements to Our Veteran Estimates and Projections Model

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This summary focuses on the technical aspects relating to the processing of the veteran population model. It begins with what is involved with developing the veteran projections and estimates. It includes the impact that the Government Performance and Results Act (GPRA) of 1993 has on the process and the direction for the future. This includes where the Department of Veterans Affairs intends to focus future projections and give examples of the type of social-economic variables that we would like to add to the model.

The Department of Veterans Affairs (VA) develops estimates and projections of veterans to satisfy the demand for the distribution of the veteran population and a legal requirement. The methodology uses a variation of the cohort survival-rate method. Projections are developed at the national, state, and county levels. The current model projects three demographic variables by three geographic levels. At the national, state, and county levels, projections are derived by age group, gender, and period of service.

The veteran population model was automated in the 1970s. This involved the use of contracted hardware/mainframe support, COBOL programming/procedural language, dedicated terminals for remote access, and one to two days turnaround time. By the 1980s, the model was converted totally to in-house use. The process included use of the VA Data Processing Center in Austin, Texas. The model conversion initially used COBOL, but it was then converted to SAS/Interpretive language. The model was run on the mainframe. The system process consisted of a projections cycle and an estimates cycle. For the projections cycle, the files that were generated included separations, national and state runs, county runs, file management, quality control, and reports. For the estimates cycle, the files include updated separations, national and state runs, county runs, file management, quality control, and reports.

The resource requirements for this system were great. Among the items to be considered were storage, space, processing staff, time, and cost. The program code was nonstructural. It was difficult to change assumptions. In addition, the model was not parameter driven and lacked modular coding. Overall, the system required extensive maintenance and was resource dependent.

As a result, the Department of Veterans Affairs is considering changing over to a personal computer (PC) environment. The major advantages of a PC platform are faster processing, greater programming control, modular coding, generalized coding, parameter driven, portability to end users, and no system constraints. However, there are startup considerations to converting to a PC platform such as choice of software language, model development, end user file formats, dissemination, and training.

In addition to improvements in hardware and software, the Department of Veterans Affairs would like to provide model enhancements. These include social-economic veteran characteristics such as race, income, and education. Our objective would be to provide timely and flexible projections that would assist policy makers when crises occur such as in Bosnia and Kosovo. Moreover, our proposed changes in methodology would consist of greater use of non-VA administrative and other databases, model-based subnational projections, and VA workload projections based on veteran population projections.

Forecasting and Analysis of Military Recruiting Plans and Programs

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This summary addressed the forecasting requirement for the military, forecasting methodology, recruiting challenge, and the requirements for the future. At the beginning of each fiscal year, the service recruiting program and budget submissions are submitted to the Office of the Secretary of Defense. The next step is to do a program analysis and evaluation. Two questions are paramount. First, do the proposed program and budget achieve accession mission? This is done by comparing the forecast and the requirement. Second, is the program cost-effective? This is achieved by comparing the cost-effective budget to proposed budget. Then, three questions are considered to determine if policy changes are necessary in the recruiting program. These include: (1) are additional resources needed; (2) should recruit quality marks be altered; (3) and would a different resource mix be cost-effective?

The forecasting methodology includes economic assumptions, enlistment supply models, and costs. The economic assumptions require forecasts of the youth population, unemployment rate of population of 16 years and over, military earnings, civilian earnings, DoD deflators for pay, and advertising cost. The enlistment supply model parameter estimates are based on preliminary findings of the Navy College Fund Evaluation study conducted by Clemson University. Costs reflect the cost-effective budget that is estimated to meet contract, workload, or requirement.

The forecasting model has four components linked in a spreadsheet framework. The components are as follows:

*gross contract calculations and recruiting budgets
*economic assumptions
*enlisted supply model parameter estimates
*minimum cost budget computations.

The forecasts and cost-effective budgets are computed by fiscal year. The model is able to compare requirements to forecast and program budgets to minimum cost budgets and provide timely feedback.

When forecasts are compared to accession goals provided the Army, Navy, Marine Corps, and the Air Force, they either indicate success or a shortfall of recruiting objectives. These situations pose recruiting challenges. These challenges may be met by considering different policy options such as reduction from high quality accessions from current policy level or increasing programmed resources currently planned for the fiscal year. This can include new initiatives such as additional recruiting funds, boosted incentives, and expanded bonus program.

The requirements for the future include standardizing the definitions of inputs between service budget submissions and the Office of the Secretary of Defense Forecasting Model and updating estimates of the enlistment supply. This includes an evaluation of the Navy College Fund and a study of the effectiveness of military advertising. Both projects are scheduled to be completed by Fall of 1999.

In addition, we are considering new model definitions. This will include new variables such as the college bound population and the veteran population and Census region supply models. Another requirement for the future is the addition of inter-service effects to the forecasting model.

Concurrent Sessions I

THE NORTH AMERICAN INDUSTRY CLASSIFICATION SYSTEM (NAICS)—Abstract

Chair: John R. Kort
Bureau of Economic Analysis

Panelists:

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Bureau of the Census, U.S. Department of Commerce

Richard L. Clayton
Bureau of Labor Statistics, U.S. Department of Labor

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The North American Industry Classification System (NAICS)

Chair: John R. Kort
Bureau of Economic Analysis, U.S. Department of Commerce

In 1992, the U.S. Office of Management and Budget (OMB) formed the Economic Classification Policy Committee (ECPC) and mandated it to undertake a "clean slate" examination of industry classification in the United States. The ECPC was chaired by the Bureau of Economic Analysis, with a member from the Bureau of the Census and the Bureau of Labor Statistics. Later, as NAFTA was passed, the United States joined with its trading partners Canada and Mexico to form a trilateral team composed of members from the U.S. ECPC, Canada's Statistics Canada, and Mexico's Instituto Nacional de Estadistica, Geografia e Informatica (INEGI) to jointly develop a common set of industry classifications for the economy of North America. The resulting new industry classification system--NAICS--was announced by OMB in April 1997. With the issuance of the 1997 economic censuses early in 1999, its implementation is beginning.

This session will first describe NAICS, its history, development, underlying concepts, and how it revises/replaces the Standard Industrial Classification (SIC) system, in use in the United States since the late 1930's, and how it compares to other industry classification systems in use in Europe and the Pacific Rim. It will then describe the U.S. statistical system's plans for implementation of NAICS, starting with the publication of information from the 1997 economic censuses in 1999, to and through the last phase of implementation in 2004. The panelists will discuss what economists in North America can expect in terms of coverage of new industries and sectors, discontinuities in historical series, plans for geographic series in each of the three agencies--Census, BLS, and BEA--and implications of the new classification system for economists and other social scientists everywhere.

Panelists:

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Bureau of the Census, U.S. Department of Commerce

Richard L. Clayton
Bureau of Labor Statistics, U.S. Department of Labor

John R. Kort
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ECONOMIC FORECASTING ISSUES

Chair: Karen S. Hamrick
Economic Research Service, U.S. Department of Agriculture

Fertility and Long-Term Economic Assumptions,
Tim A. Dowd, U.S. Joint Committee on Taxation
R.M. Monaco, INFORUM/University of Maryland

An Update on the Business Cycle,
Nancy L. Morrison & Foster Morrison, Turtle Hollow Associates, Inc.

The Role of the Unemployment Rate and the Capacity Utilization Rate
in Explaining Inflation,
Paul A. Sundell, Economic Research Service, U.S. Department of Agriculture

FERTILITY AND LONG-TERM ECONOMIC PROJECTIONS

Timothy Dowd, Joint Committee on Taxation[1]
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For the past several years, there has been considerable concern that the federal old-age, disability and survivors insurance programs (OASDI), popularly known as Social Security, will not be able to meet their promised future financial obligations. The general outlines of the problems are well-known. In a nutshell, a major part of the problem facing OASDI is a rapid increase in the number of beneficiaries relative to the workforce that pays the taxes to support the trust funds. The projected increase in the elderly dependency ratio (the ratio of the number of people aged 65 and over to the number of people aged 16 to 65) is generally attributed to the jump in fertility rates that occurred from 1946 to 1964, known as the Baby Boom and the natural aging of the population.

The problems facing the social insurance trust funds are not imminent, according to the most recent round of reports of the public trustees of these funds. The Old Age, Survivors, and Disability Insurance (OASDI) Trust Funds are expected to be insolvent as a group in 2034, although the Disability Insurance trust fund is expected to be insolvent by 2020. The widely-discussed problems are actually anticipated problems. The seriousness of the future insolvency problems depends crucially on projections of several economic and demographic variables.

Economic and Demographic Assumptions

Future values of economic and demographic variables that underlie social insurance trust fund projections are developed in the Office of the Actuary at the Social Security Administration (SSA), in conjunction with input from other federal agencies and invited experts. While it is difficult to characterize precisely the methods used to develop the projections, it is fair to say that there has yet been no published set of equations or a model that form the basis of the economic and demographic assumptions. It appears that the predominant method for developing the projections that underlie the projected insolvencies amounts to examining past trends on a variable-by-variable basis and establishing judgements about the future course of the variables in light of the past trends. It's important to emphasize that, for the most part, projections are done variable-by-variable, except where there is a simple linking function that creates a larger aggregate from several sub-pieces. Thus, while the projection for real GDP growth is created as the sum of labor force growth, labor productivity growth and several assumptions about "links," there does not appear to be a mechanism that relates, say, productivity growth to labor force growth, or even mortality changes to projected changes in economic well-being.

A judgmental, largely univariate approach can produce excellent forecasts. In contrast to the intuition of some (especially those with models), there is virtually no evidence that model approaches, even those models that might include co-movements between the variables of interest, generally result in forecasts superior to single-variable extrapolations or judgement alone. Thus, there is a good possibility that the current methods and forecasts for the economic and demographic variables are about the best that can be expected. This would imply that the expected trust fund insolvency dates are about as accurate as can be expected.

The chief difficulty with the judgmental, variable-by-variable approach arises when you want to examine the effects of a change in one assumption, say, economic growth, on the trust fund balance. A naive approach would be to assume that all other assumptions/projection values would remain the same. Thus, an increase in labor force growth would be projected to have effects on the trust fund balances, but not on labor productivity, inflation, mortality, or even fertility. A more comprehensive view would allow for the effects of interaction among the variables, including interactions between economic and demographic variables.

A simple, straightforward case can be made that demographic assumptions like mortality and fertility should be conditioned on economic variables like wages, inflation, interest rates, and economic growth. There are few who would argue that rising levels of economic well-being, measured by real GDP per

[1] The views expressed in this paper are solely the authors', and do not reflect the views of the Joint Committee on Taxation, nor of any member of Congress.

capita, are usually associated with falling mortality rates (across countries, and, to some extent, over time within countries).

Fertility decisions today obviously influence the size of the labor force, roughly 15-to-20 years in the future. Perhaps equally important to changes in the size of the population is the effect that children have on the labor supply of their parents. Increased fertility today, resulting in more children, may increase or decrease the size of the labor force depending on the decisions households make about childcare. Changes in labor force participation are likely to affect younger women most and men and older people least. Thus, fertility movements can affect the age and gender composition of the current labor force, as well as influencing the size of the future work force directly. Overall, the economy is certainly influenced by the growth in the labor force, and some authors have speculated that productivity of the workforce is inversely related to the average age of the workforce.

How important is it to capture interactions between economic and demographic variables? This paper attempts to answer that question, at least partially, by examining the relationship between fertility behavior and economic variables. First, we briefly review a recently developed empirical model of fertility behavior. Next, we use the 1999 Social Security Administration economic forecasts to help develop a projection of fertility through 2050 and compare the projection with the most recent SSA projection concerning fertility behavior. Finally, we comment on the differences between the projections, and whether such differences would lead to different public policy views of the Social Security insolvency problem.

The Fertility Model

The empirical model of fertility we use here was developed in Dowd (1999), which contains a complete description of the theory and econometric estimation. In this paper, we summarize that work. Dowd's work draws on the work of Becker and Lewis (1973) who take an economic view of the fertility decision. In short, this approach views the decision to have a child like the decision to buy a durable good. Such a view suggests that variables like the wage rate, household income (excluding wage income), and a host of other demographic/economic variables including age, race, residence state, and marital status determine the demand for children, and thus affect the fertility rate.

The model of fertility used in this paper was developed in two main steps. First, three cross-section regressions using data from the 1970, 1980, and 1990 censuses was carried out. Appendix A discusses the estimation results and the technique used to estimate the cross-section regressions.

In the second stage, we developed a time series of predicted age-specific fertility rates for women for each age from 1968 to 1993, using historical data for the independent variables in the cross-section equation and the estimated cross-section parameters. This time series of cross-section-predictions was then used as an independent variable in a time series regression on observed age-specific fertility rates. The time series regression also included the age-specific female wage rate and the unemployment rate.

Economic variables were found to have a significant effect on fertility decisions in the cross-section estimation. The cross-section work found that the wage rate and household income have elasticities of -3.5 percent and 0.1 percent respectively. Age and marital status are probably the most important determinants of fertility. A 1 percent change in the age of the average woman from 34.2 to 34.6 years of age results in an almost 5 percent decline in the probability of observing a birth. Similarly a 1-percent increase in the age of the average woman from 20 to 20.2 years of age results in a 2.2 percent increase in the probability of observing a birth. However, holding everything else constant, increasing the age of a woman from 20 to 34 reduces the probability of observing a birth by over 18 percent. The relationship between age and fertility is not linear. Specifically, the effect on fertility of a rising age increases until about age 26 and declines thereafter (no fertility is assumed after age 50). Similarly, for a woman with "average" demographic and wage characteristics, marrying increases the probability of having a child by 162 percent. Thus, fertility rates will move depending on the values of these other variables.

In the time series, the three variables included in the regression captured more than 80 percent of the variation in the age-specific fertility rates, with the exception of age 16 (38 percent) and age 45 (around 70 percent). The time series regressions suggested stronger negative relationships between the female wage and fertility than estimated from the cross-section alone.

Table 1 shows the overall elasticities on the total fertility rate of changes in wages (assuming that female wages maintain their historical relationship to

total wages), the unemployment rate, and personal income. Each entry shows how the total fertility rate (number of babies born per thousand women of childbearing age) changes for a 1- percent change in the variable of interest. The table shows that, according to the model outlined above, a one-percent higher wage, maintained through 2050, reduces the total fertility rate by between 4 and 5 percent.

The Most Recent SSA Projections

The SSA produces three main alternative views of the future: (1) Low Cost, (2) Intermediate, and (3) High Cost. The authors of the *Annual Report* characterize the Intermediate projections as the "best estimate of the future course of the population and the economy (p. 53)." The Low and High-Cost alternatives provide bounds for the projections of the health of the trust funds. In the Low Cost alternative, demographic and economic assumptions are chosen to make the costs of OASDI low. From the point of view of the solvency of the OASDI funds, this may be regarded as the "lucky" scenario, in which all the economic and demographic factors evolve to minimize outlays and increase revenue for the trust funds. The scenario may not be lucky from the view of society at large, however. A key reason that OASDI costs are kept low is that the Low Cost scenario incorporates higher mortality rates than are assumed in either of the other two scenarios.

Like the Low Cost alternative, the High Cost scenario provides a cost upper-bound for the program. This alternative combines elements such as lower labor productivity and labor force growth with lower mortality rates than the other scenarios. While the High and Low Cost alternatives bracket the Intermediate projections, no attempt is made to assess the probability of either the Low or High Cost alternatives. Further, the differences between the High/Low and the Intermediate do not incorporate any fixed probability, either for a single variable, or for the trust fund balance. So, while the High and Low projections bracket the Intermediate projections, it is not possible to establish the differences between them as confidence intervals of any specified width.

We take four main variables directly from the SSA projections and use them in the fertility model. These are: (1) the growth in real wages, (2) labor force participation for men and women, (3) real GDP growth, and (4) the unemployment rate. Various assumptions were made to make the SSA projections compatible with the variables needed in the cross-section and time-series regressions. For example, we assumed that all wages moved at the average rate. Personal income is assumed to grow at the same rate as GDP. Minor adjustments were made to the SSA unemployment rate too. Labor force participation rates for men and women were taken from unpublished data behind the 1997 trust fund report. There appears to be only a slight change in the labor force assumptions between the 1997 and 1999 reports, so using the available 1997 data in the place of the 1999 data will change predicted fertility only slightly.

Table 2 shows the most recent assumptions from the 1999 report of the public trustees for those variables that are most important to the fertility model. The table shows that SSA associates higher fertility rates with lower costs for the OASDI programs in the long run. While the total fertility rate in the Intermediate case is expected to fall slightly (from 2.03 in 1999 per woman to 1.9 per woman in 2050), fertility is expected to rise in the Low-Cost scenario and fall sharply in the High Cost scenario. In the short run, an increase in fertility actually raises the cost of the program slightly and pushes the insolvency date closer to the present. That is because dependent children and dependent children survivors are covered by Social Security programs. However, taking a longer run view, higher fertility rates tend to increase the revenue of the program by creating a larger workforce.

Chart 1 shows the history and Intermediate SSA projection for the total fertility rate. The projection suggests that, while the total fertility rate will remain above the levels of the mid-1970s through the late 1980s, it will stay close to 2000 (per thousand women) over the next 50 years. The total fertility rate is not expected to approach the average rate from 1920 to 1970, roughly 2750.

Chart 2 compares the predictions of the fertility model outlined above with the SSA Intermediate projection for total fertility. The predictions from the fertility model were developed using the SSA Intermediate economic assumptions to drive the model, as described above. Chart 2 shows that the fertility model predicts lower fertility than the SSA Intermediate alternative based on the other variables projected in the Intermediate case. The fertility model projects lower fertility than the SSA Intermediate case initially, and shows little long-run tendency to change between 2000 and 2015. After 2015, the fertility model shows a trend toward lower fertility, which deviates progressively from the SSA Intermediate case. By 2050, fertility predicted by the model is about 15 percent lower than that predicted by the SSA Intermediate case.

Chart 3 compares the three SSA cases with the predictions of the fertility model, based on SSA Intermediate economic variables. The chart shows that the fertility model predictions generally lie about mid-way between the SSA Intermediate and High Cost cases, and are quite far from the Low Cost projections.

As a further step, we generated predictions from the fertility model using the High (Low) Cost economic and demographic variables. That is, we used the High (Low) SSA projections for the four variables listed above to generate predictions of fertility. These predictions are shown in Chart 4, which shows the 2050 fertility rates for each prediction along with the SSA fertility rate used as part of the High (Low) Cost projection. As the chart shows, allowing the economic and demographic projections to influence the fertility prediction results in predictions that move closer to the Intermediate result. That is, model-predicted fertility is higher than SSA projections in the High Cost alternative, and lower than SSA projections in the Low Cost alternative. Interestingly, the model predicted fertility results for the High Cost are actually higher than the model results using the Intermediate SSA projections, and the model predicted fertility results for the Low Cost are lower than the model results using the intermediate SSA projections. Thus, Chart 4 illustrates that allowing interaction among the projected variables would, in this case, reduce the High-Low differences in the projected variables and in the trust fund outcomes themselves.

Implications and Conclusions

In this paper, we asked: Are there substantial differences between the current set of SSA projections about fertility behavior and a model of fertility behavior that attempts to account for economic influences like wages and income? In other words, we addressed the issue of whether there is a kind of inconsistency between SSA's economic assumptions and their fertility assumptions. Such a question is reasonable, given that there appears to be no mechanism to enforce consistency, except the judgement of those making the assumptions in the first place.

We think several major conclusions emerge.

- The fertility model predictions and the SSA Intermediate projections are fairly close. That suggests the SSA Intermediate assumptions about fertility have captured the "average" economic effects embodied in their economic assumptions.

- The fertility model predicts declining fertility over the very long term. In contrast, by design, SSA holds constant their fertility (and other) projections after about 2020. The widening gap between the fertility model -- based on SSA Intermediate assumptions -- and the SSA Intermediate projection suggests that SSA might want to consider moving their "hold constant" date out to 2050 or so, in order to capture trends that might reasonably be expected in the long term.

- The differences between the fertility model predictions and the Intermediate case (the fertility model always predicts lower fertility) suggests that SSA may want to consider lowering their Intermediate fertility projection, especially if the "hold constant" date is extended.

- Given that the fertility model predicts lower fertility than the Intermediate case -- even with Intermediate economic assumptions -- SSA might want to consider lowering their fertility projections associated with both the High Cost (low fertility) alternative and the Low Cost (high fertility) alternative.

- The evidence from Chart 4 suggests that the High Cost and Low Cost bounds are exceptionally wide, and that allowing fertility to be determined partially by the values of the other projected variables would result in considerably narrower bounds.

In this paper we have explored only one avenue of interaction between demographics and the economy, and examined the effects on an important set of projections that are often used for public policy purposes. In our future work, we intend to build a simulator that will allow full, joint determination of the important demographic and economic variables that underlie projections of the OASDI trust funds.

Appendix A: Cross Section Fertility Regression Results

Cross section fertility equations were estimated using data from the Integrated Public Use Microdata Sets (IPUMS). These equations were estimated using the Heckit procedure to adjust for sample selection bias. Details of the estimation and the equation are found in Dowd (1999), especially pages 20-33.

Logit Estimation of the Probability of Birth (Log(p/1-p)=XB, where p=Prob(birth=1))

	1970	1980	1990
Elasticities			
Age	9.904	14.226	15.593
Age Squared	-8.724	-10.432	-11.412
Wage OLS	-0.524	-3.037	-2.315
Other Hhld Income	0.028[1]	0.060	0.074
Tax Value State Exemption	-0.040[3]	-0.172	0.010[3]
State Tax Rate	-0.255	-0.106	-0.166
EITC		0.027	0.027
Education	0.423	1.358	1.332
Married	57.6	219.9	160.9
Married Quarter 1	693.4	69.7	
Married Quarter 2	771.7	76.9	
Married Quarter 3	743.6	78.5	
Married Quarter 4	722.4	72.8	
Husband Labor Participation	83.2	117.8	194.4
No. Children 1< age < 5	82.6	75.0	130.8
No. Children age >= 5	11.3	25.5	34.4
Twins at First Birth	-7.1[3]	36.8	12.7[2]
Twins at Second Birth	-10.6[3]	-39.7	-21.9
First 2 children same gender	1.8[3]	14.2	7.0
Two or More Children	-51.7	-60.7	-58.8
Husb. Part. * No. Child 1<age<5	-44.6	-34.8	-47.1
Husb. Part. * No. Child age>=5	-18.4	-35.1	-37.1
Teenager	-33.4	9.8	52.7
- 2 Log L			
Intercept and Covariates	132493	152539	163059
Intercept Only	177361	199490	204391

Source: Dowd (1999), p. 224.

All estimates are significant at the 1% level unless noted otherwise below. 1 Significant at the 5% level. 2 Significant at the 10% level. 3 not significant. Other variables not shown here are dummy variables for immigration status, metro status, racial and ethnicity background, and for the 1980 and 1990 years indicators of English speaking capabilities, and school attendance in the previous year. In addition, all of the full specifications included occupational and state dummies. Married in quarter 1-4 are all statistically different from each other in both 1970 and 1980. EITC is created for all women regardless of number of children in household.

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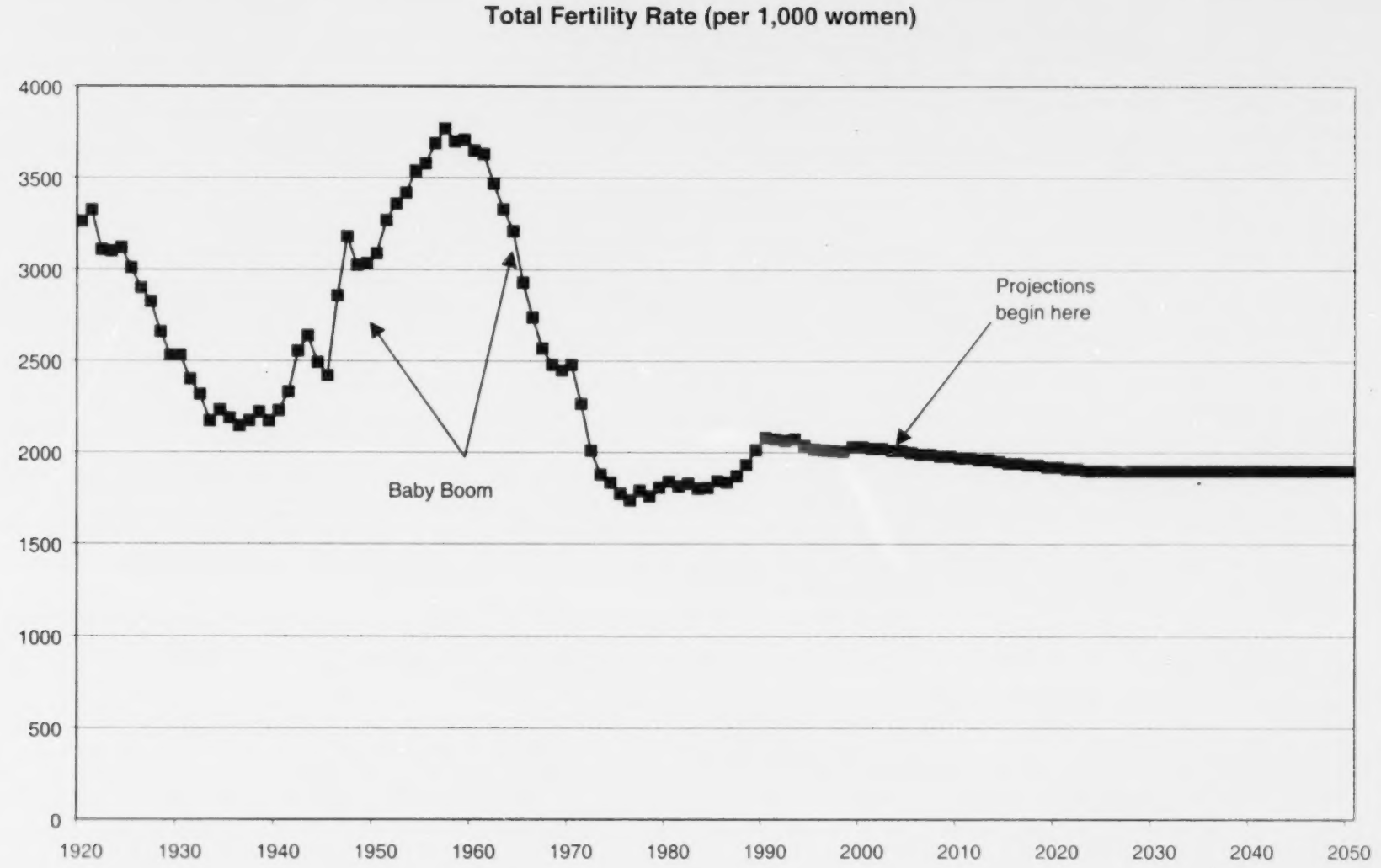
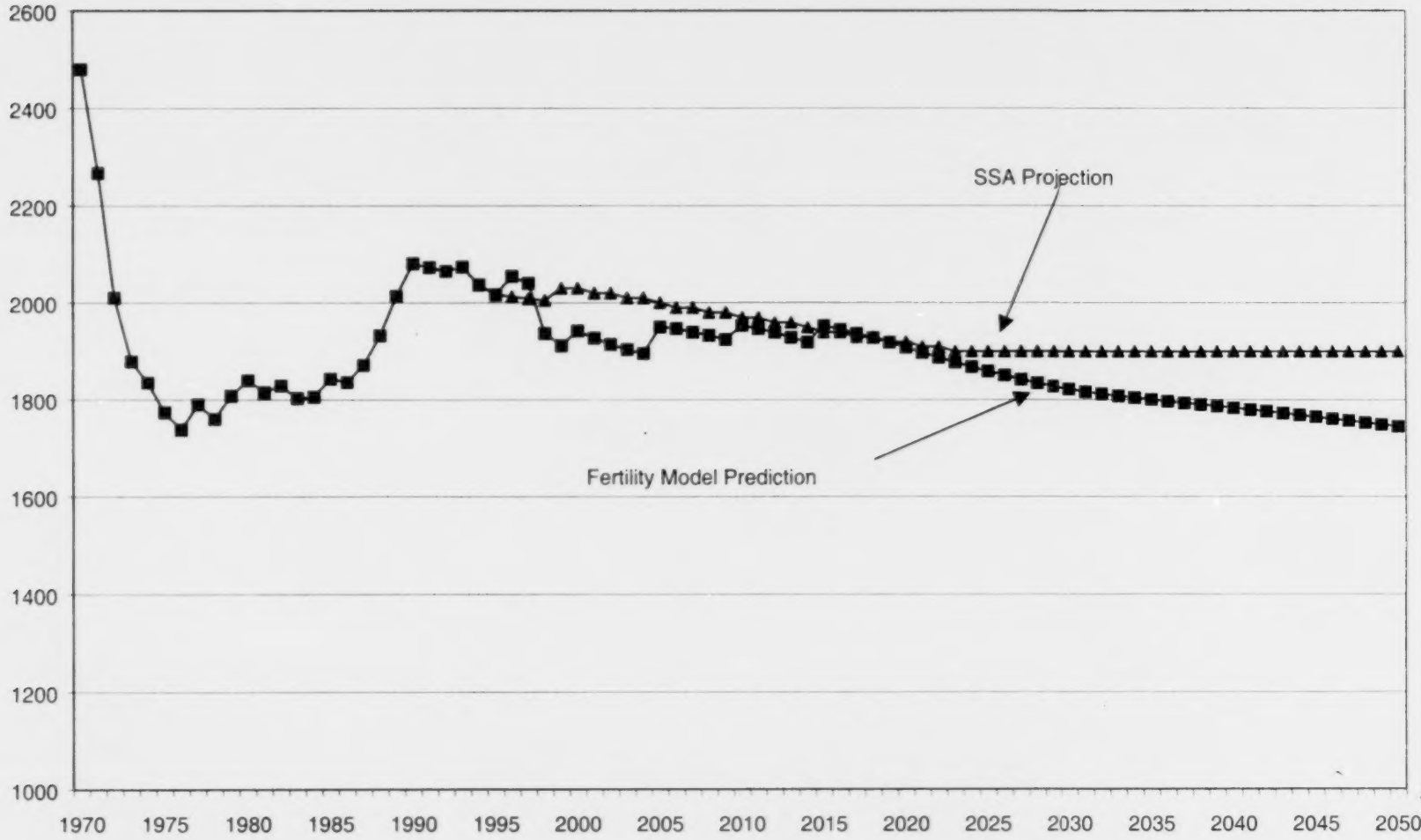
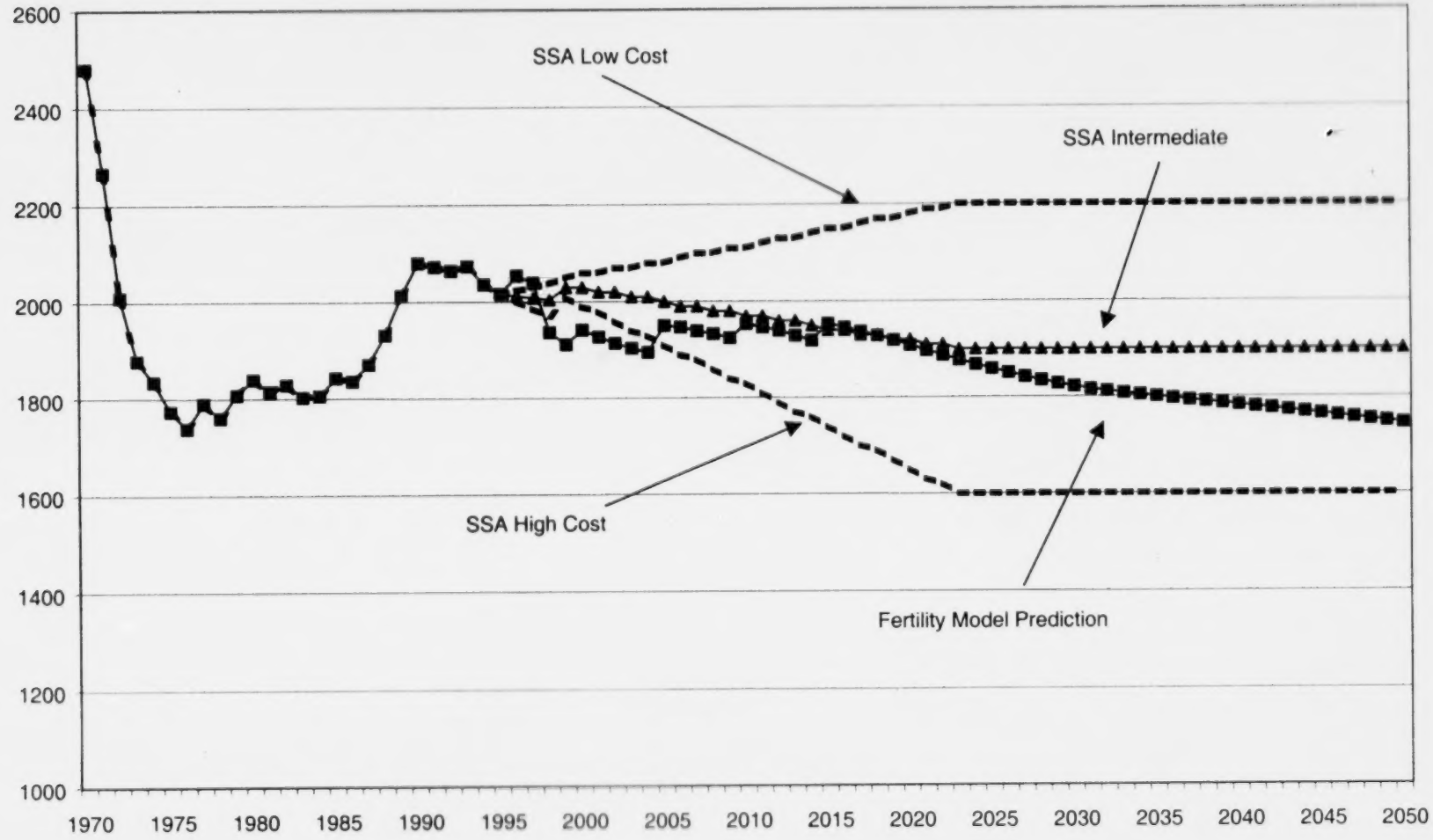

Total Fertility Rate (per 1,000 women)
4000
3500
3000
2500
2000
1500
1000
500
0
1920
1930
1940
1950
1960
1970
1980
1990
2000
2010
2020
2030
2040
2050
Projections
begin here
Baby Boom

Comparing SSA and Fertility Model Projections



Comparing SSA Alternatives and Fertility Model Prediction



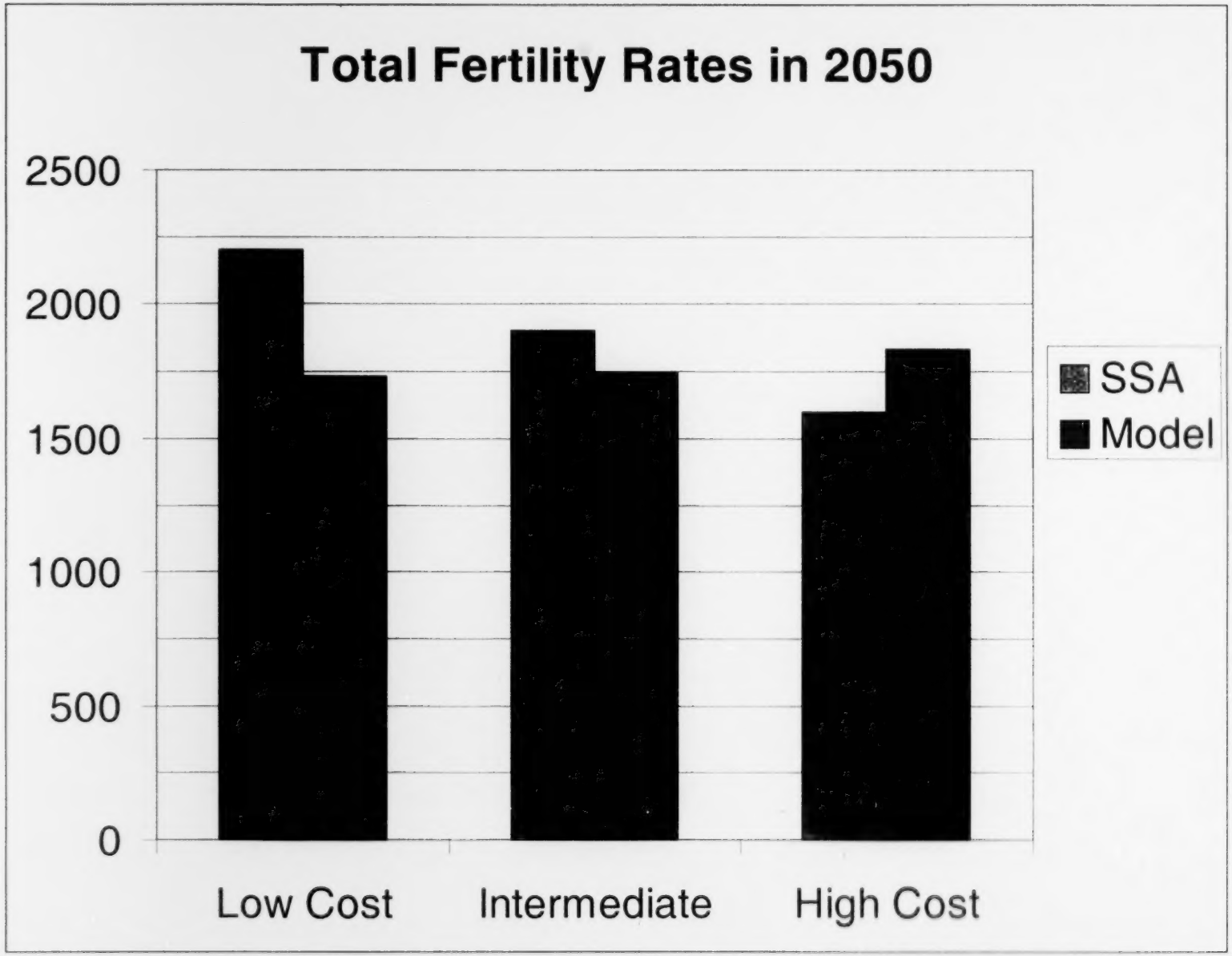

Total Fertility Rates in 2050
2500
2000
1500
1000
500
0
Low Cost
Intermediate
High Cost
SSA
Model

Table 1: Model Elasticities

Model Elasticities From 1% increase 1993 - 2050			
Year	1997	2020	2050
Total Fertility Rate Elasticity with respect to			
Wages, real	-4.1	-3.9	-4.7
Unemployment	-3.0	-3.4	-4.3
Personal Income, real	0.5	0.9	1.2
Source: Dowd (1999). p. 146			

Table 2: Selected SSA Economic and Demographic Assumptions

	1999	2005	2010	2020	2050
Real GDP Growth, annual growth rate in year					
Low	2.6	2.5	2.3	1.9	2.1
Intermediate	3.4	2.0	1.8	1.4	1.3
High	2.1	2.4	1.3	0.9	0.4
Unemployment rate, percent					
Low	4.4	4.5	4.5	4.5	4.5
Intermediate	4.6	5.5	5.5	5.5	5.5
High	4.6	6.5	6.5	6.5	6.5
Real Wage Growth, annual growth rate in year					
Low	1.6	1.3	1.5	1.4	1.4
Intermediate	1.0	1.0	1.0	0.9	0.9
High	0.7	1.1	0.5	0.4	0.4
Labor Force Growth, annual growth rate in year					
Low	1.3	1.0	0.8	0.3	0.5
Intermediate	1.2	0.9	0.6	0.2	0.1
High	1.1	1.0	0.5	0.1	-0.3
Total Fertility Rate, births per thousand women					
Low	2050	2080	2110	2180	2200
Intermediate	2030	2000	1970	1920	1900
High	2010	1910	1830	1650	1600

Source: *1999 Annual Report of the Board of Trustees of the Federal Old-Age, and Survivors Insurance and Disability Insurance Trust Funds*, pp. 58-59, 62-63.

AN UPDATE ON THE BUSINESS CYCLE

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1. Introduction

The business cycle is the long recognized deviation of economic activity from the trend. One definition of a recession is two or more successive quarters where the inflation-adjusted GDP (gross domestic product) declines. This sort of definition is good because it does not depend on the trend model. For example, the moving average is a very good trend model, but its proper reference point is the middle of the sampling period. Half of the sampling period may be a much longer time than the range of validity of the forecast. An alternative is another low-pass filter, the ramp filter, whose reference point is the end of the sampling period [Morrison & Morrison, 1997]. The ramp filter is optimized for forecasting; other trend models that can and have been used include differencing and polynomial regression.

Business cycles are disruptive to both individuals and organizations. All human beings need to have food and shelter on a continuing basis; we cannot hibernate. To survive, everybody needs a regular minimal income, however provided. Recessions cause job losses, underemployment, and other hardships which most strongly affect low-income people.

Major governments and established businesses can easily survive recessions and even depressions by borrowing. Interest rates usually will be low. Marginal businesses, however, may collapse. Weak governments may devalue and print money, eventually producing hyperinflation and capital flight. During the past few years all these events have occurred in Mexico and the once formidable Asian "Tigers." Japan remains mired in a recession and Europe has high unemployment. In sharp contrast, the U.S. economy has been booming for the most recent quarters (1998, III & IV; 1999, I) reported by DoC (the U.S. Department of Commerce).

Private sector forecasters and academics who have business clients are very much attuned to the business cycle. By contrast, those federal agencies whose missions are not closely tied to the level of economic activity have been able to ignore it, at least until the past decade. The federal budget has evolved over the years so that non-discretionary items have grown and most of these expenses are higher during recessions, just when tax revenues are dropping. As a consequence, every federal forecaster now has some interest in the business cycle, which will affect appropriation levels, even if the agency mission is not in the realm of economics.

2. Dynamics of the Business Cycle

Many economists have attempted to "explain" the business cycle. The alternating build up and sell off of inventories has often been mentioned. Excess capacity due to overinvestment is another possibility. A whole host of factors can be examined, but it is not possible to offer any kind of scientific proof that any one thing is the principal cause. Even the statistical correlations do not always hold [Samuelson, 1976, pp. 249-268].

Various fiscal and monetary policies have been used in an attempt to smooth out the business cycle. The basic concept is for the national government to restrain booms with higher taxes and thereby build up surpluses. When the recession does come, then government will be able to pay for infrastructure projects and provide unemployment insurance, as well as other "safety net" benefits, without having to run deficits. One problem with this concept is lack of fiscal and political discipline; spending programs win elections and tax increases lose them.

Monetary policy also has been used to combat the business cycle. Expanding the money supply and reducing interest rates can stimulate growth, but more so during a period of expansion than during a recession. One casualty of monetary policy has been the purchasing power of the dollar and all other currencies. It is difficult to quantify this over long periods, since technology and product mix have changed drastically, but it is safe to say that anyone holding fixed-income investments

for more than a decade has lost buying power with the exception of the period 1932-1941.

There is good reason to doubt that the business cycle can ever be eliminated. This is assuming a level of determinism that just does not happen in complex, dynamical systems. Modern physics has shown that we do not have a "clockwork" universe. Chaos and randomness abound. Einstein was wrong on this one. God does not merely play dice; He is an habitual gambler.

To the extent that supply and demand do define "laws," they provide "clockwork" that is full of slack and subject to backlash. The whimsy of consumers, or even of professional purchasing agents, does not seem to average out to smooth curves. The natural world contributes its own random forces, what with climatic variations and natural disasters.

Econometric time series, after detrending, can be subjected to spectral analysis. ACFs (autocorrelation functions) can be computed and used in forecasting. For a perfectly predictable process the power spectrum is a few spikes (Dirac delta functions). A completely unpredictable process has a flat power spectrum; that is the definition of "white noise." Of course, "white noise" does not exist in the real world; it has infinite energy. It is a useful concept for linear systems theory, however. "Pink noise" is what one actually observes; it is cut off at the higher frequencies, which are blue in the optical spectrum [Morrison, 1991, pp. 280-302].

We have found that all the econometric time series we have examined have fairly smooth, gradually decreasing power spectra. This is what one expects if the law of supply and demand is approximated by the classic cobweb model (a damped, linear oscillator) disturbed by a white (really pink) noise input. If the damping is nonlinear, and weaker for small variations from equilibrium, the filtering action of the market dynamics will be weaker most of the time. Large deviations are damped more strongly, producing the limited short-term predictability and long-term stability observed in economic, ecological, and climatological systems. Quantitative analysis of these data may require simulations with nonlinear ODEs (ordinary differential equations) [Morrison, F. & N.L. Morrison, 1999].

Linear filtering may still be used as a forecasting method, since all it requires is a reasonably stable power spectrum (or ACF). However, to understand the limits to controlling the business cycle and ways to avoid depressions will almost certainly require looking at the nonlinearities in the economic system and also in ecological and geophysical systems. The caveat here is to construct models and simulations that are minimal so that the rounding and truncation errors do not take control of the calculations at the very first step.

3. A Minimal Business Cycle Model

Aggregation is one of the ways to simplify overly complex systems so they can be modeled by equations of limited accuracy and arithmetic of limited precision. Using only two variables is ideal. One represents "everything" and the other the feedbacks that control it. The conceptual model is the Volterra predator-prey system [Davis, 1962; Luenberger, 1979]. Upon linearization at the equilibrium point, this degenerates into the harmonic oscillator.

The Volterra system is two nonlinear ODEs. The prey equation is exponential growth with a quadratic feedback. The predator equation has a quadratic growth term and an exponential decay term to model deaths due to old age. The solutions are periodic for positive initial conditions, offering an explanation for observed population cycles. Such a model is really qualitative, despite the level of mathematical sophistication. Obviously, the growth rate of the predator population is limited, no matter how large the available prey. However, in the days before computers, a solvable system was to be preferred to a more precise one.

The next question is why the cycles persist, since the equations are unstable. Unstable how? Even a slight perturbation could destroy the periodicity, converting the solution into a collapse into the equilibrium. What preserves the observed periodicity? One possibility is that the perturbations create a limit cycle, not a collapse [Mesterton-Gibbons, 1989, pp. 154-7]. Another is that random noise inputs keep the cycle "alive." These are not mutually exclusive hypotheses. Noise always exists at some level and, except for rare cases like the motions of the major planets, is a powerful influence. This is one reason few physical or biological and no social sciences will ever attain the precision levels of celestial mechanics.

Dynamically speaking, the business cycle is a similar problem. However, the "cycles" observed do not exhibit regular periods. Neither do all population data sets. This implies that the undisturbed market dynamics do not yield a limit cycle, but a collapse to equilibrium.

Such qualitative analysis should always be done before committing equations to paper, let alone code to a computer. The modeler needs a catalogue of simple dynamical models, as well as analytical and computer skills. Mathematical equations can easily take on a life of their own, devoid of any connection to reality.

In the case of the business cycle, it is not necessary to reinvent any wheels to get a two-variable model. Indices of leading and coincident indicators were compiled decades ago by DoC, though the effort now continues under the aegis of The Conference Board in New York City. An index of lagging indicators also is being kept; some economists prefer it and use it in their forecasting, often in an inverted form.

The coincident index acts as a stand-in for GDP, with the advantage of having monthly, rather than quarterly, values. The leading index, then, must represent the feedbacks that eventually will curtail growth and render it negative for two or more quarters. In such a model, the huge number of variables is not only aggregated, it is ***edited***.

To create a business ***cycle*** model, the indices must be detrended. To do this we applied a 60-point ramp filter to the logarithms of the indices of leading and coincident indicators [Morrison & Morrison, 1997, 1998]. Then a phase plane plot is created, producing a ***phase angle***, the most important parameter in the business cycle, as well as an amplitude. This is an unambiguous, if not perfect, answer to the question, "Where are we in the business cycle?" Revisions made to the indices by both The Conference Board and its predecessors at DoC have left these phase angles virtually unchanged, considering the possible precision they could offer [Morrison & Morrison, 1998].

4. What Has the Model Done for Us Lately?

The question now is, what does the model tell us about the period since the last Federal Forecasters Conference, which has seen significant growth, low inflation, low unemployment, and a booming stock market. And what, if anything, does it suggest about the future?

In February 1996 the model suddenly decayed into the origin, after being on a fast track for the recession-prone fourth quadrant. This did happen shortly after the current stock market boom began in December 1995. Needless to say, we were surprised by both. Figure 1 illustrates the behavior of the model since January 1990.

Stalls in the model are nothing new. Significant ones occurred in 1964-66, 1981, 1990, and 1994, but these did not occur near the origin [Morrison & Morrison, 1997]. However, the only sure thing about business cycles is that no two are the same. This recent stall has lasted longer than any of these others too.

To try to see what has been going on, we made a new graph at a much larger scale. Figure 2 is this plot of the model during the stall that still persists. The results do not look like a classic "random walk," but perhaps like two random walks in succession. Qualitatively, this is reminiscent of the famous Lorenz "butterfly" pattern.

One possibility is that the business cycle finally has been tamed. What is mysterious is how this was suddenly done in February 1996. Did the U.S. Treasury and the Federal Reserve Bank start doing everything just right? How did the stock market anticipate this? And how has the U.S. economy remained so stable while much of the world has been stagnant or in decline?

Numerous writers in the *Wall Street Journal* have suggested that the new information and service economy is inherently less cyclical than manufacturing. Others claim that just-in-time inventory management has eliminated business cycles. Both may be true to some extent.

One possibility, of course, is that the model has failed. If so, a recession will start and be noticed while the model stays on dead center or even goes the wrong way.

Our interpretation is that the model is accurately reflecting the anomalous U.S. prosperity. For one thing, flight capital from Asia and Latin America has helped to offset the chronic U.S. balance of payments deficits. Money has poured into the stock market rather than into consumer purchases, so inflation has remained tame. In other words, the period 1996-1999 (to date) has been one of those rare cases where everything goes right.

We might call this the "Whiz Kids theory," where Alan Greenspan and Robert Rubin are the Whiz Kids and the inspiration is the 1950 Philadelphia Phillies who won their first pennant in 35 years. The question is what will happen next? After winning that championship in the last game of the regular season on a home run by a player who was traded the next year

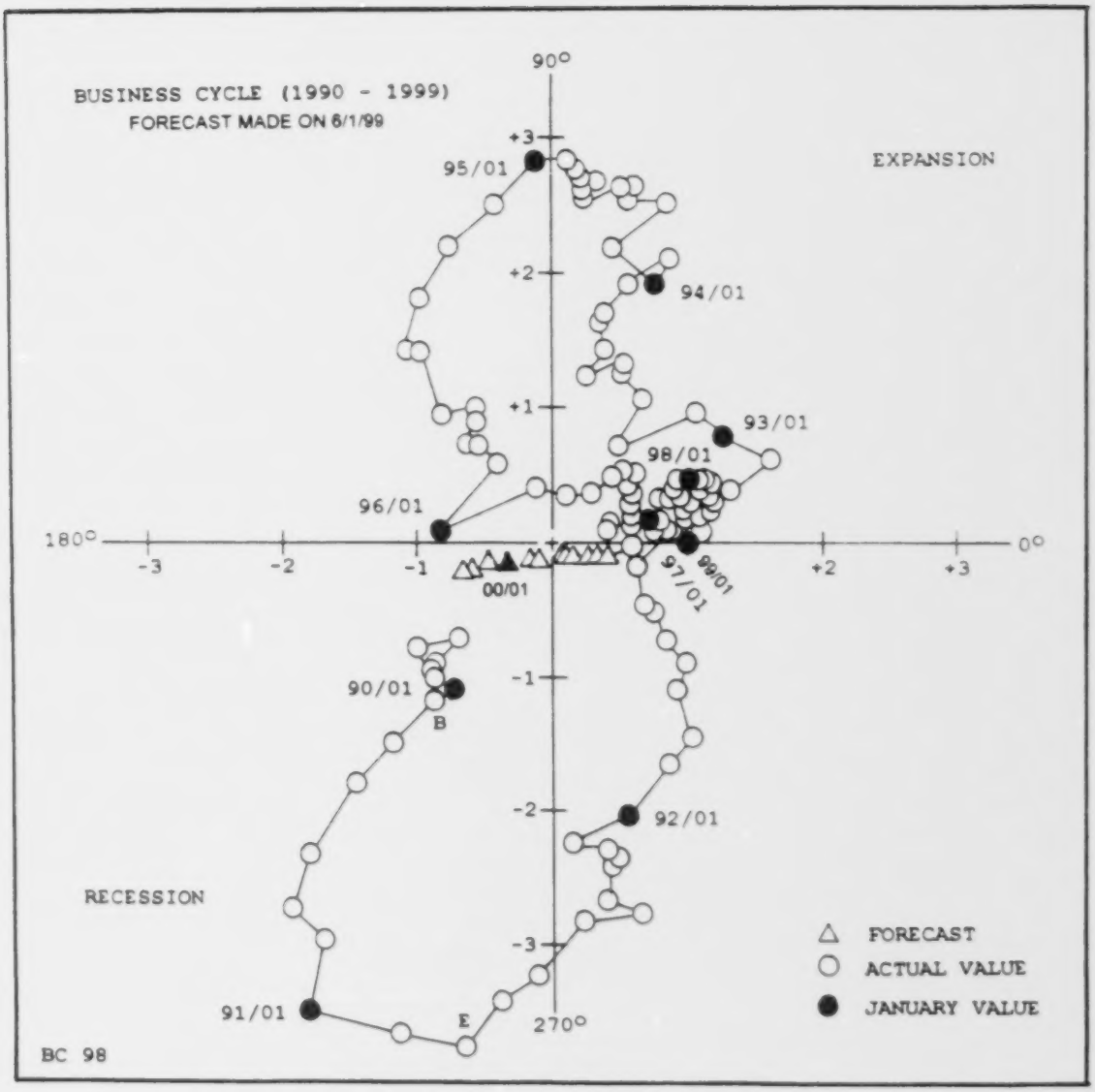

Figure 1. The current cycle with June forecast. The business cycle model is a phase plane plot of detrended leading and coincident indicators, as x- and y-coordinates, respectively. Normal cycles follow a counterclockwise roughly elliptical path with occasional stalls and reversals. Time is indicated along the cycle path. Expansions occur in the first quadrant (between 0° and 90°) and contractions in the third quadrant (between 180° and 270°). Other angles (second and fourth quadrants) denote transition periods. An "official" (National Bureau of Economic Research) beginning of a recession is indicated by a label "B" and an end by "E."

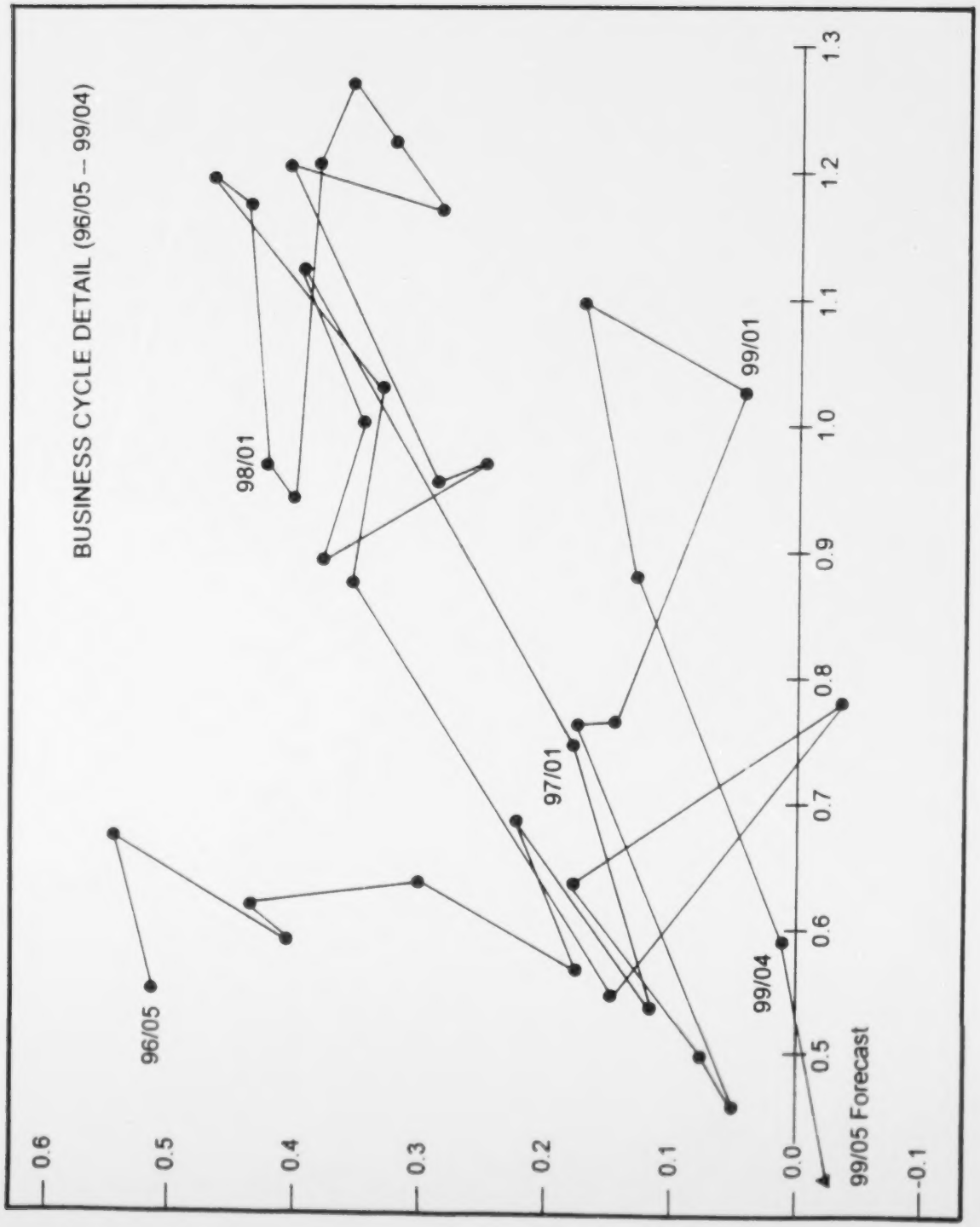

Figure 2 (displayed with x-axis vertical) Larger scale plot of the recent (May 1996 — April 1999) business cycle stall. One point from the forecast (May 1999) is included. Note that the indicators used to construct the model are released about two months after the fact, so a forecast is needed to provide an estimate of the current value.

(Dick Sisler), the Phillies were blown out of the World Series in four straight.

We doubt that the business cycle has been tamed, because we suspect that the necessary level of control does not exist. However, our time series forecasts will not predict the start of the next recession, since the whole apparatus amounts ***dynamically*** to turning off the noise and letting the system decay to equilibrium. Since the system is already there, the forecast is not going to go anyplace until powerful new signals appear in the data. This property of time series forecasts is well worth knowing and demonstrates their limits.

One thing all this indicates is that better dynamical models of the business cycle are needed. These may well already exist at the Federal Reserve or Treasury, but for obvious reasons have not been published. Private vendors do supply such forecasts, and charge hefty subscription fees, but many institutions, both public and private, would want to keep their models proprietary.

One tool we have devised for creating such models is the CNC (continuous numerical continuation) ODE solver. A brief presentation of it is being made at this Conference.

5. The Business Cycle: Interpretation and Forecasts

Those who have done forecasts with real data know that the results are rarely as precise as one desires. Methods that produce error estimates, and many good *ad hoc* methods do not, usually let you know that in advance. And, of course, future data values often differ from the forecast by one or two or more standard deviations.

Certain modeling techniques can introduce instabilities. Polynomial regression for trend models is an obvious example. Differencing to detrend data can amplify noise. Even an *ad hoc* method that is stable and reliable will be giving forecasts that are more a product of the mathematics than the data.

Forecasters should understand what dynamical properties are assumed by a methodology. In the case of linear filtering, as mentioned above, it means turning off the noise input to a damped linear oscillator. However, one may consult a text and find only a minimum variance derivation of the equations with no direct reference to the dynamical interpretation. The noise is effectively turned off because it is assumed to have *zero expected value*, but the variance estimate climbs asymptotically to the noise signal power because the *mean square value* of the noise is assumed to remain constant.

What does this mean for the business cycle or other forecasting applications? A forecast is often more useful for detecting anomalies or trend shifts than prediction. The message from the business cycle model is that things are abnormally stable compared to what has been the case over the past 40 years, despite financial and economic crises around the world in a period of increasing "globalization." One hypothesis is that the U.S. has been uniquely successful in attaining stable growth, despite the troubles elsewhere. A second is that the "Whiz Kids" at the Federal Reserve and Treasury have been unusually lucky. Which is correct? Place your bets, as many have done in the stock market.

Table 1 gives recent GDP values, growth rates, and a forecast. Table 2 provides recent numerical values for the business cycle model, as well as a forecast.. The GDP forecast was generated by a 32-point linear filter, where the ACF is obtained from a 128-point FFT (fast Fourier transform). Both indices are forecast with 16-point linear filters; the ACF comes from a 512-point FFT. The trend model is a 60-point ramp filter in both cases.

Quarter	Value	σ	Growth Rate
1999/I	7754.7	0.0	4.07%
1999/II	7782.8	57.7	1.46%
1999/III	7850.9	95.1	3.55%
1999/IV	7901.6	121.5	2.61%
2000/I	7915.3	140.5	0.70%
2000/II	7973.8	154.3	2.99%
2000/III	8000.5	162.9	1.35%
2000/IV	8012.4	169.5	0.60%
2001/I	8055.0	175.2	2.14%
2001/II	8092.7	177.1	1.89%
2001/III	8143.3	178.5	2.52%
2001/IV	8143.7	178.6	0.02%

Table 1. Forecasts of GDP in billions of chained 1992 dollars, including the most recent estimated value, 1999/I.

Date	P_L	P_C	R	θ	Quad
Observed					
1995/01	-0.075	2.828	2.829	91.5	II
1995/02	-0.423	2.517	2.552	99.5	II
1995/03	-0.760	2.204	2.331	109.0	II
1995/04	-0.975	1.814	2.060	118.3	II
1995/05	-1.083	1.432	1.796	127.1	II
1995/06	-0.999	1.409	1.727	125.3	II
1995/07	-0.825	0.940	1.251	131.3	II
1995/08	-0.557	1.017	1.160	118.7	II
1995/09	-0.568	0.911	1.073	122.0	II
1995/10	-0.651	0.732	0.979	131.6	II
1995/11	-0.620	0.741	0.966	129.9	II
1995/12	-0.404	0.579	0.706	125.0	II
1996/01	-0.831	0.019	0.831	178.7	II
1996/02	-0.040	0.437	0.439	95.2	II
1996/03	0.046	0.327	0.330	82.0	I
1996/04	0.308	0.383	0.491	51.2	I
1996/05	0.548	0.515	0.752	43.2	I
1996/06	0.672	0.544	0.865	39.0	I
1996/07	0.590	0.404	0.715	34.4	I
1996/08	0.614	0.439	0.755	35.6	I
1996/09	0.636	0.300	0.704	25.2	I
1996/10	0.566	0.175	0.592	17.2	I
1996/11	0.686	0.226	0.723	18.2	I
1996/12	0.535	0.115	0.547	12.1	I
1997/01	0.748	0.176	0.769	13.2	I
1997/02	1.120	0.390	1.187	19.2	I
1997/03	1.002	0.346	1.060	19.0	I
1997/04	0.893	0.379	0.971	23.0	I
1997/05	0.969	0.249	1.001	14.4	I
1997/06	0.950	0.290	0.993	17.0	I
1997/07	1.207	0.406	1.273	18.6	I
1997/08	1.169	0.282	1.202	13.6	I
1997/09	1.225	0.322	1.267	14.7	I
1997/10	1.270	0.355	1.318	15.6	I
1997/11	1.205	0.381	1.263	17.5	I
1997/12	0.940	0.403	1.023	23.2	I
1998/01	0.968	0.422	1.056	23.6	I
1998/02	1.173	0.439	1.252	20.5	I
1998/03	1.196	0.466	1.284	21.3	I
1998/04	1.030	0.329	1.081	17.7	I
1998/05	0.875	0.355	0.944	22.1	I
1998/06	0.547	0.149	0.566	15.2	I
1998/07	0.781	-0.035	0.782	357.5	IV
1998/08	0.636	0.180	0.661	15.8	I
1998/09	0.500	0.072	0.505	8.2	I
1998/10	0.457	0.050	0.460	6.3	I
1998/11	0.762	0.180	0.783	13.3	I
1998/12	0.765	0.144	0.778	10.7	I
1999/01	1.028	0.043	1.029	2.4	I
1999/02	1.099	0.171	1.112	8.8	I
1999/03	0.880	0.128	0.889	8.3	I
Observed					
1999/04	0.590	0.011	0.590	1.1	I
Forecast					
1999/05	0.400	-0.027	0.401	356.2	IV
1999/06	0.307	-0.064	0.313	348.3	IV
1999/07	0.224	-0.096	0.243	336.7	IV
1999/08	0.138	-0.059	0.150	336.6	IV
1999/09	0.055	-0.099	0.113	299.2	IV
1999/10	0.060	-0.068	0.091	311.1	IV
1999/11	-0.111	-0.120	0.164	227.1	III
1999/12	-0.186	-0.177	0.257	223.6	III
2000/01	-0.340	-0.163	0.377	205.6	III
2000/02	-0.473	-0.147	0.495	197.3	III
2000/03	-0.586	-0.204	0.620	199.2	III
2000/04	-0.595	-0.249	0.645	202.7	III
2000/05	-0.509	-0.211	0.551	202.6	III
2000/06	-0.598	-0.180	0.625	196.7	III
2000/07	-0.596	-0.139	0.612	193.1	III
2000/08	-0.685	-0.179	0.708	194.7	III
2000/09	-0.590	-0.145	0.607	193.8	III
2000/10	-0.578	-0.182	0.606	197.4	III
2000/11	-0.647	-0.218	0.683	198.7	III
2000/12	-0.710	-0.250	0.752	199.4	III

Table 2. Recent and forecast values for the business cycle state variables. P_L is the x-coordinate and P_C is the y-coordinate, which are the percent deviations from the trend of the indices of leading and coincident indicators. R is the radial coordinate and θ the phase angle in degrees; Quad is the quadrant of θ.

For federal forecasters the nature of the dilemma depends on whether the client base is the general public or the agency itself, and on what the agency mission area is. Some industries and many agencies are non-cyclical. Manufacturing is highly cyclical, so are most transportation companies.

If a recession does materialize, Treasury will see a fall in revenues and watch the hypothetical surplus disappear. Agencies that maintain the "safety net" will need more resources. If the recession is severe, there will be political pressure to start infrastructure programs, as in Japan (and during the New Deal era in the USA).

The conservative strategy is to prepare for a future one or two standard deviations on the downside. It is always easy to cope with good times. Even if the

"gloom-and-doom" crowd is finally right (and we doubt that the business cycle has been tamed or that depressions are a thing of the past), you and your organization will be better situated than most.

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THE ROLE OF THE UNEMPLOYMENT RATE AND THE CAPACITY UTILIZATION RATE IN EXPLAINING INFLATION

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Despite the unemployment rate falling in the late 1990's to its lowest level since the late 1960's, inflation continued to fall in recent years. The combination of a low unemployment rate and falling inflation has surprised the vast majority of macro economists. The apparent break in the relationship between the unemployment rate and changes in the inflation rate has caused many economists to reevaluate their views on the level of the unemployment rate currently consistent with stable inflation over the longer term. Economists have long attempted to estimate the nonaccelerating inflation rate of unemployment (NAIRU). When the unemployment rate falls below the NAIRU, tight labor markets place upward pressure on wage and non-wage benefits in excess of productivity gains, which in turn places upward pressure on inflation.

The significance of the relationship between changes in inflation and the gap between the unemployment rate and the NAIRU, as well as the stability and measurability of the NAIRU are important in policy debates concerning not only the inflation outlook, but the outlook for short-term real growth, interest rates, and exchange rates also. Current views on the usefulness of the unemployment rate and the NAIRU in predicting inflation vary significantly among economists, with increasing numbers of economists (such as Gordon, Stiglitz, and Phelps) arguing that the NAIRU has dropped significantly in the 1990's.

My empirical work extends the work of authors such as King, Staiger, Stock, Watson, and Gailbraith, who argue the NAIRU is highly variable and uncertain and thus is of very limited use as an predictor of changes in inflation. I extend their work by estimating the NAIRU with a demographically adjusted unemployment rate variable. In addition, I include a time varying nonaccelerating inflation rate of capacity utilization (NAIRCU) with a time varying NAIRU variable in my empirical work to examine their joint and individual significance in explaining changes in inflation.

The empirical work produces four main conclusions concerning the relationship between changes in inflation and the level of the unemployment rate, and capacity utilization in the manufacturing sector. First, the NAIRU is highly uncertain over time and cannot be measured with a high degree of precision. Uncertainty in estimating the NAIRU is shown by estimating time varying NAIRU's over the 1971I through 1998IV period using the Kalman filter approach. Under varying assumptions concerning quarterly variability in the NAIRU, widely differing NAIRU estimates were produced that were largely indistinguishable in their ability to explain one quarter ahead movements in inflation, as evaluated by their of their log-likelihood statistics. King, Stock, and Watson and Staiger, Stock, and Watson originally pointed out the difficulty in statistically distinguishing different time varying NAIRU estimates.

The second conclusion of my research is the variability of the NAIRU is not primarily due to demographic shifts. Some authors most notably Perry, Gordon, and Motley have argued that shifts in the proportion of workers in terms of age and sex have been sufficiently large to cause substantial variability in the NAIRU. For example, when the work force has abnormally high percentages of workers groups with higher than average unemployment rates, such as the young, the NAIRU will be higher. I constructed a demographically adjusted unemployment rate series that used average long-term proportions of unemployed workers by age and sex to control for demographic shifts. The demographically adjusted unemployment rate displayed only very marginally more explanatory power in explaining changes in inflation than the aggregate unemployment rate for workers 16 and over reported by BLS.

The third and most important conclusion of my research is that the nonaccelerating inflation rate of capacity utilization rate for manufacturing (NAIRCU) has much more explanatory power in explaining changes in inflation than the NAIRU. High rates of capacity utilization typically entail the use of marginally less productive resources and the opportunity for greater profit margins in markets where firms have some market power in determining prices (McElhattan, and Corrado and Mattey). High rates of capacity utilization also influence the aggressiveness that firms display in negotiating labor market contracts. When capacity is tight, firms are more concerned with their ability to provide sufficient goods in order to maintain long-term customer relationships and therefore firms are more likely to agree to wage demands in excess of productivity increases. Profitability tends to be high when capacity utilization is high, which further increases the likelihood that firms will acquiesce to higher

wage demands.

In this study, the inclusion of the gap between capacity utilization and the estimated NAIRCU was highly significant in predicting inflation. Equally important, the inclusion of the gap between actual capacity utilization and the estimated NAIRCU caused the estimated gap between the unemployment rate and the NAIRU to become insignificant in predicting changes in inflation.

Fourth, the final equation for the change in inflation (as measured by the GDP chain weighted GDP deflator) explained over 56 percent of the variation in the change in inflation over the 1971I-1998IV period. Explanatory variables in this final equation in addition to lagged changes in the rate of inflation, included real relative price shock variables, and the gap between the current rate of manufacturing capacity utilization and an estimated fixed NAIRCU of 81.3 The real relative price shock variables included shifts in real food, energy, and import prices, as well as differences between overall inflation and growth in unit labor costs. The capacity utilization gap variable was significant at the one percent level and the residuals from the inflation equation were free of serial correlation and fit the recent years of decelerating inflation well. As was the case for the change in inflation equations that did not include relative price shock variables, the inclusion of the gap between the unemployment rate and the NAIRU was not significant when the gap between manufacturing capacity utilization and the NAIRCU was included in the equation.

Statistical Methods and Discussion of Empirical Results

Estimating the NAIRU .

The NAIRU is estimated using a stochastic coefficients models whereby both the NAIRU and NAIRCU are postulated to follow a random walk. The models are estimated using the Kalman filter procedure. The Kalman filter uses a linear state variable updating procedure whereby the error in the observational equation, in this case U_t from the change in inflation equation, is used to update the prior estimate of the state variables, in this case the NAIRU and NAIRCU variables. An excellent introduction to the Kalman filter is provided in Meinhold and Singpurwalla. The base equation for the change in inflation takes the form of equation 1.

(1) $\Delta INF_t = A + B_i \Sigma L^i \Delta Inf_{t-1} + C_j \Sigma L^j (UN - NAIRU)_t + U_t$:

where ΔINF_t is the change in inflation,, UN is the unemployment rate and $NAIRU_t = NAIRU_{t-1} + e1_t$. $e1_t$ is a normally distributed error term that is serially uncorrelated. L^i is the lag operator and is used to form the lag polynomial $(1-B_i L^i)$, which is postulated to produce characteristic roots that are less than one in absolute value. Characteristic roots that are less than one in absolute value insure that the difference equation is stable in the long run such that if the unemployment rate is equal to the NAIRU, inflation will also be stable in the long-run. Furthermore, the impact of a one period shock to the observational error term will decay over time. The base unemployment rate in this study is the BLS seasonally adjusted aggregate unemployment rate for workers 16 years of age and older.

In estimating the NAIRU in equation 1, various plausible values for the variance of $e1_t$ are specified in advance and the log- likelihood statistics of these estimated equations for various levels of NAIRU variability are then compared. Best overall fit in terms maximizing the likelihood function is one important criteria used in model selection. The constant NAIRU model is nested in the general time varying model of the NAIRU. If the variance of $e1_t$ is zero, the NAIRU is constant over time. The constant NAIRU model may be estimated by an OLS regression where the change in inflation is regressed on a constant and current and lagged values of the unemployment rate. The estimate of the NAIRU in the constant NAIRU case estimated by OLS is equal to negative of the constant term divided by the sum of the coefficients on the unemployment rate variable.

The dependent variable used in this study is the change in the inflation rate. Some authors have used the level of inflation while others have used the change in inflation as dependent variables in their NAIRU equations. In order to use standard t statistics in hypothesis testing, the dependent variable should be stationary and all explanatory variables either stationary or cointegrated (Banerjee et al., pp. 187-190).

In determining whether the dependent and independent variables were stationary, the sequential unit root testing procedure recommended by Enders (pp. 254-258) was used. Ender's sequential unit root testing procedure begins by testing the time series for a unit root in a general time series model that includes drift and time trend terms. If the unit root model is not rejected in this general model, various t and F tests are performed to test for the presence of time trend and drift terms, along with various other unit roots tests that depend upon whether drift and or time

trend terms are present. The sequential unit root tests indicated that inflation as measured by the GDP and CPI deflators both contained unit roots and thus required differencing to achieve stationarity.

Empirical Results

Figure 1 shows the empirical results for equation 1 for various assumed levels of variability in the NAIRU. In the figure, NAIRU00 corresponds to the constant NAIRU over time case. NAIRU01 corresponds to quarterly variation in the NAIRU of .01 percent, while NAIRU02 corresponds to assumed quarterly variation in the NAIRU of .02 percent, etc. It is unlikely that factors that influence the NAIRU over the intermediate term, such as the supply and skills of labor, worker uncertainty, and shifts in underlying productivity growth, will shift substantially enough on a quarterly basis to produce quarterly variability in the NAIRU of more than .04 percent. A slightly better fit was achieved by including the contemporaneous (t) and lagged unemployment rate (t-1). The results of this regression is shown as regression 6 in Table 1. The positive coefficient on the lagged unemployment rate indicates that in addition to the level of the unemployment rate, the change in the unemployment rate also impacts inflation (Fuhrer, p.46).

Most importantly, for the contemporaneous and lagged unemployment rate NAIRU equations, the log-likelihood estimates for the contemporaneous and lagged unemployment rate NAIRU equations,were not sensitive to assumptions concerning the variability of the NAIRU's. Specifically, although the constant NAIRU assumption produced slightly superior log-likelihood statistics, the log-liklihood statistics of the constant NAIRU were not significantly better than those assuming a positive variance for the NAIRU.[1] Thus, the results in Table 1 indicate the NAIRU as it relates to inflation (as measured by the GDP deflator) is highly uncertain.

Table II shows similar results using the CPI-U as the inflation measure. None of the assumed NAIRU variance equations is statistically superior in terms of its log-liklihood. The overall fit of the CPI equations in terms of their R^2 is higher than GDP chain weighted deflator equations. Much of the better fit of the CPI is due to the smaller more homogeneous market basket of goods and services in the CPI-U relative to the GDP chain weighted deflator and the reduced sensitivity of the CPI-U to relative price shocks, especially relative price shocks from imports. Consumption contains a greater proportion of services than GDP and domestic services face less foreign competition than goods. In addition, the CPI-U is less affected by falling computer prices than the GDP deflator.

Table III and Table IV substitutes a demographically adjusted unemployment rate for the aggregate 16 and over unemployment rate used in the Table's I and II. Shifts in the share of the work force between groups with widely different unemployment rates over time is likely to have some impact on the NAIRU. If over time however, employment is fairly substitutable between various labor groups as job training increases the substitutability of workers by age and sex, the impact of demographic factors will be more muted over time.

For this study, a demographically adjusted unemployment rate was generated as a weighted average of four age classifications each for men and women. Specifically the average relative proportion of the unemployed for male and female unemployment falling in the 16 to 19 age group, the 20 to 24 age group, the 25 to 54 age group, and the 55 and over were computed over the 1971I through 1998IV period. These average proportions by sex and age group were then multiplied by the actual quarterly unemployment rates for the respective sex and age class to derive a demographically adjusted unemployment rate. This approach is similar to the procedure used by Motley in deriving his demographically adjusted unemployment rate. Comparison of NAIRU estimates using the demographically adjusted unemployment rates in Tables III and IV were little different from the results using the aggregate unemployment rate in Table I and II. The similar overall results for the demographically adjusted unemployment rate regressions and difficulty in choosing a definitive variance for the NAIRU in Tables III and IV indicated that problems in identifying the NAIRU are not primarily related to demographic factors.

The gap between the actual rate of capacity utilization in manufacturing and the estimated nonaccelerating inflation rate of capacity utilization for manufacturing (NAIRCU) was added to base equation to obtain equation 2.

[1] The log-likelihood ratio test states that 2 times the log likelihood ratio of the two competing models will be distributed as a $\chi 2$ with k degrees of freedom. If the likelihood statistics are very similar and the competing models differ by only one assumed parameter in the estimation process, we have little confidence in clearly choosing one model over the other based on the likelihood statistics. Since we are constraining only one parameter, the state variance parameter, the likelihood ratio statistic has one degree of freedom and a 5 percent critical value of 3.84. Therefore, the log-likelihoods must differ by 1.92 to be statistically different from one another at the five percent significance level.

(2) $\Delta Inf_t = a + B_i \Sigma L^i \Delta Inf_{t-1} + C_j \Sigma L^j (UN - NAIRU)_t + D_k \Sigma L^k (CAP - NAIRCU)_t + U_t$:

where $NAIRU_t = NAIRU_{t-1} + e1_t$ and $NAIRCU = NAIRCU_{t-1} + e2_t$. e1 and e2 are normally distributed error terms that are serially uncorrelated.

Capacity utilization is the ratio of actual output to sustainable maximum output or capacity. Since the demand for services is far less variable over the business cycle than the demand for goods, the gap between actual capacity utilization and the NAIRCU provides information on the overall tightness of aggregate demand relative to aggregate supply in product markets. In addition, because the FRB's industrial capacity and capacity utilization measures are survey based, changes in the amount and quality of the industrial capital stock are reflected in the actual and sustainable capacity measures used to derive capacity utilization. Manufacturing capacity utilization is typically used in studies examining the link between inflation and capacity utilization since it does not include capacity utilization for utilities and mining. Capacity utilization for utilities and mining is much more volatile on a quarterly basis.

The inclusion of capacity utilization term (CAP) is especially important given the break in the relationship between the manufacturing capacity utilization rate and the unemployment rate since 1995. The break in the relationship between manufacturing capacity utilization and the unemployment rate is shown in Figure 2. Since 1995, while the unemployment rate has fallen sharply, capacity utilization has declined. The fall in capacity utilization since 1995 reflects the very strong pace of business investment in the mid to late 1990's coupled with strong foreign competition resulting from the strong dollar and overall relatively mild foreign growth. Over the 1971I-1994IV period the correlation between capacity utilization and the unemployment rate was -0.88. Over the 1995I-1998IV period their correlation has been 0.48. The break in the relationship between the unemployment rate and capacity utilization since 1995, provides us an opportunity to more easily and accurately disentangle the roles of capacity utilization and the unemployment rate in the inflation process.

Table V presents the empirical results of estimating equation (2) for the change in inflation as measured by the GDP deflator. Most striking is the finding that the inclusion of the capacity utilization NAIRCU gap term is significant at the one percent level and its inclusion eliminates the significance of the unemployment rate NAIRU gap terms. Specifically, the unemployment rate terms becomes individually and collectively insignificant. In addition, the estimate of the NAIRCU in Table 5 displays less long-term drift for various levels of assumed quarterly variability in the NAIRCU then the NAIRU series estimated in Table I. Therefore the capacity utilization - NAIRCU relationship is stronger and more stable than the unemployment rate- NAIRU in explaining changes in inflation.

A valid further examination of the role of capacity utilization and the unemployment rate in the inflation process is to include relative price shocks in the analysis. In the absence of important relative price shocks, the estimated short-term NAIRU and NAIRC may change due to temporary large shifts in relative inflation for especially important commodities and services. Table VI presents the results of estimating equation 3 below, which includes other terms Z_t such as relative price shock terms for food energy and import prices and the recent the gap in the growth of output prices as measured by the GDP chain weighted deflator and unit labor costs.

(3) $\Delta Inf_t = a + B_i \Sigma L^i \Delta Inf_{t-1} + C_j \Sigma L^j (UN_t - NAIRU)_t + D_k \Sigma L^k (CAP - NAIRCU)_t + E_l \Sigma L^l Z_t + U_t$:

where $NAIRU_t = NAIRU_{t-1} + e1$ and $NAIRCU = NAIRCU_{t-1} + e2_t$

The relative price shock term for food and energy is defined as the growth in consumption chain weighted deflator less food energy minus growth in the overall consumption chain weighted deflator. Growth in real import prices is defined as growth in chain weighted import prices relative to growth in the chain weighted GDP deflator. As was the case with model 2, the unemployment rate NAIRU gap terms were insignificant. Therefore, the unemployment rate NAIRU gap terms were dropped from Table VI. The model results indicate a one time percentage point increase in real food prices will cause a small short-term increase in inflation that does not lead to permanently higher inflation. Thus inflation will temporarily rise and then fall in response to short-tem higher inflation for food, energy, and imports.

The impact of labor market conditions is captured by the deviation between overall inflation and growth in unit labor costs. Rising growth in unit labor costs relative to output prices indicates in general declining profit margins which will put upward pressure on inflation in coming quarters. The gap between the level of capacity utilization and the constant NAIRC term of 81.3 is significant at the one percent level. Overall the equation explains over 56

percent of the variation in the change in next quarter's inflation.

Figure 3 shows the residuals from equation 3. Overall, the residuals were relatively small and randomly distributed. The residuals exhibited no autocorrelation as indicated by first and higher order Breusch-Godfrey tests. The forecast errors were especially small for the 1997 and 1998 period. Overall the largest residuals in absolute value terms were produced in the early 1970's, largely due to the phasing in and phasing out of the Nixon price controls.

In separate regressions, I examined the role of productivity shocks on inflation by adding productivity shocks to equation 3. Productivity shocks were measured in two forms. The first measurement of productivity shocks was the deviation in quarterly productivity growth in private nonfarm business relative to average quarterly labor productivity growth for that business cycle. Due to difficulties in measuring productivity in the service sector as well as to capture the impact of rising capital productivity in recent years, I also included Tobin's q as an additional productivity shock variable in equation 3. While the coefficients on these productivity variables were of their expected negative sign in explaining changes in inflation, the productivity variables were not significant and thus were not included in table VI.

Conclusions

My empirical work indicates that the NAIRU is very uncertain and because its uncertainty the NAIRU is of limited use to policy makers. On the other hand, the NAIRCU is much more stable and powerful in explaining inflation. The model with relative price terms predicted changes in inflation one quarter ahead extremely well, especially for the recent past. Many potential GDP estimates make heavy use of the NAIRU in their derivation. Given the vastly superior performance of capacity utilization in predicting inflation, policy makers and econometricians need to make greater use manufacturing capacity and manufacturing capacity utilization in predicting inflation and potential output.

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Table I
Base Regressions For Change in Inflation
Dependent Variable: Change in Inflation As Measured by GDP Deflator
Unemployment Variable: Aggregate Unemployment rate 16 and Over
(1971I-1998IV)

	Contemporaneous Unemployment Rate Regressions					Contemporaneous and Lagged Unemployment Rate Regressions				
Regression No.	1	2	3	4	5	6	7	8	9	10
Quarterly Var. of NAIRU	0.00	0.01	0.02	0.03	0.04	0.00	0.01	0.02	0.03	0.04
Constant NAIRU	6.30					6.30				
NAIRU 1998IV	6.30	5.43	5.14	5.00	4.92	6.30	5.38	5.03	4.86	4.76
Other Explanatory Variables (t-statistic)										
Constant	0.006	0.092	0.100	0.091	0.078	-0.005	0.086	0.103	0.102	0.095
	(0.05)	(0.60)	(0.58)	(0.48)	(0.39)	(-0.05)	(0.56)	(0.59)	(0.54)	(0.47)
Change in $Inf._{t-1}$	-0.191	-0.202	-0.206	-0.207	-0.207	-0.172	-0.182	-0.185	-0.185	-0.185
	(-2.47)	(-2.58)	(-2.65)	(-2.68)	(-2.70)	(-2.23)	(-2.34)	(-2.39)	(-2.42)	(-2.43)
Change in $Inf._{t-2}$	-0.351	-0.359	-0.362	-0.364	-0.364	-0.335	-0.343	-0.345	-0.346	-0.346
	(-4.12)	(-4.14)	(-4.20)	(-4.25)	(-4.29)	(-3.61)	(-3.65)	(-3.72)	(-3.76)	(-3.78)
Unemploy. $Rate_t$	-0.276	-0.302	-0.310	-0.312	-0.312	-0.690	-0.725	-0.739	-0.745	-0.748
	(-2.92)	(-2.89)	(-2.89)	(-2.85)	(-2.81)	(-2.56)	(-2.62)	(-2.62)	(-2.61)	(-2.58)
Unemploy. $Rate_{t-1}$						0.440	0.451	0.459	0.467	0.472
						(1.57)	(1.61)	(1.66)	(1.69)	(1.72)
Log Likelihood	-165.22	-165.45	-165.62	-165.82	-166.02	-164.08	-164.24	-164.38	-164.55	-164.72
St. Error of Reg.	1.062	1.059	1.060	1.062	1.065	1.052	1.048	1.048	1.050	1.052
Durbin-Wat. Stat.*	2.05	2.04	2.08	2.06	2.07	2.05	2.06	2.07	2.08	2.09

*Durbin's h statistics also rejected the presence of first order autocorrelation. The failure of the h statistics to indicate autocorrelation is not surprising given the closeness of the Durbin Watson statistics to 2. Breusch-Godfrey tests also rejected the hypothesis of first and higher order autocorrelation.

Table II
Base Regressions For CPI-U
DependentVariable: Change in Inflation as Measured by CPI-U
Unemployment Variable: Aggregate Unemployment rate 16 and Over
(19711-1998IV)

Regression No.	1	2	3	4	5
Quarterly Var. of NAIRU	0.00	0.01	0.02	0.03	0.04
Constant NAIRU	6.35				
NAIRU 1998IV	6.35	5.52	5.15	4.97	4.85
Other Explanatory Variables (t-statistic)					
Constant	-0.005	0.106	0.138	0.140	0.134
	(-0.03)	(0.40)	(0.42)	(0.38)	(0.33)
Change in Inflation$_{t-1}$	-0.242	-0.252	-0.256	-0.257	-0.256
	(-2.36)	(-2.31)	(-2.30)	(-2.29)	(-2.28)
Change in Inflation$_{t-2}$	-0.391	-0.399	-0.403	-0.404	-0.404
	(-4.62)	(-4.21)	(-4.11)	(-4.05)	(-4.01)
Change in Inflation$_{t-3}$	0.177	0.167	0.163	0.162	0.162
	(1.82)	(1.62)	(1.54)	(1.50)	(1.48)
Unemployment Rate$_t$	-1.984	-2.030	-2.055	-2.066	-2.07
	(-4.46)	(-4.39)	(-4.39)	(-4.39)	(-4.38)
Unemployment Rate$_{t-1}$	1.657	1.676	1.690	1.702	1.712
	(3.56)	(3.59)	(3.63)	(3.65)	(3.68)
Log Likelihood	-209.56	-209.78	-209.92	-210.06	-210.21
St. Error of Reg.	1.579	1.578	1.580	1.583	1.586
Durbin-Watson Stat*.	2.06	2.07	2.08	2.09	2.09

* As was the case for the base change in inflation for the GDP deflator, the Breusch Godfrey test for autocorrelation failed to indicate the presence of autocorrelation.

Table III
Alternative Base Regressions For GDP Deflator
DependentVariable: Change in Inflation As Measured by the GDP Chain Weighted Deflator
Unemployment Variable: Demographically Adjusted Aggregate Unemployment rate 16 and Over
(19711-1998IV)

Regression No.	1	2	3	4	5
Quarterly Var. of NAIRU	0.00	0.01	0.02	0.03	0.04
Constant NAIRU	6.30				
NAIRU 1998IV	6.30	5.67	5.44	5.31	5.22
Other Explanatory Variables (t-statistic)					
Constant	0.015	0.060	0.062	0.055	0.048
	(0.14)	(0.39)	(0.35)	(0.29)	(0.24)
Change in Inflation$_{t-1}$	-0.189	-0.191	-0.191	-0.191	-0.190
	(-2.45)	(-2.44)	(-2.46)	(-2.47)	(-2.47)
Change in Inflation$_{t-2}$	-0.347	-0.348	-0.348	-0.348	-0.347
	(-3.73)	(-3.69)	(-3.73)	(-3.76)	(-3.77)
Unemployment Rate$_t$	-0.711	-0.730	-0.737	-0.740	-0.741
	(-2.75)	(-2.74)	(-2.71)	(-2.67)	(-2.64)
Unemployment Rate t-1	0.426	0.448	0.457	0.464	0.469
	(1.60)	(1.68)	(1.73)	(1.76)	(1.79)
Log Likelihood	-163.20	-163.81	-164.13	-164.40	-164.64
St. Error of Reg.	1.044	1.045	1.048	1.050	1.053
*Durbin-Watson Stat.	2.06	2.07	2.08	2.09	2.09

* Breusch-Godfrey tests failed to indicate the presence of autocorrelation.

Table IV
Alternative Base Regressions For CPI Deflator
DependentVariable: CPI-U
Unemployment Variable: Demographically Adjusted Aggregate Unemployment rate 16 and Over
(19711-1998IV)

Regression No.	1	2	3	4	5
Quarterly Var of NAIRU	0.00	0.01	0.02	0.03	0.04
Constant NAIRU	6.40				
NAIRU 1998IV	6.40	5.81	5.67	5.61	5.60
Other Explanatory Variables					
Constant	-0.096	-0.033	-0.075	-0.126	-0.175
	(-0.52)	(-0.10)	(-0.18)	(-0.27)	(-0.34)
Change in Inflation$_{t-1}$	-0.363	-0.363	-0.365	-0.366	-0.368
	(-4.08)	(-4.09)	(-4.14)	(-4.19)	(-4.24)
Change in Inflation$_{t-2}$	-0.478	-0.480	-0.482	-0.484	-0.486
	(-6.74)	(-6.50)	(-6.51)	(-6.53)	(-6.55)
Change in Inflation$_{t-3}$	0.030	0.025	0.024	0.023	0.023
	(1.29)	(1.08)	(1.01)	(0.97)	(0.95)
Unemployment Rate$_t$	-2.054	-2.10	-2.125	-2.139	-2.148
	(-4.70)	(-4.69)	(-4.72)	(-4.73)	(-4.73)
Unemployment Rate$_{t-1}$	1.512	1.559	1.573	1.581	1.586
	(3.51)	(3.56)	(3.58)	(3.57)	(3.56)
Log Likelihood	-209.63	-210.33	-210.66	-210.91	-211.13
St. Error of Reg.	1.580	1.587	1.593	1.598	1.601
Durbin-Watson Stat.	1.91	1.93	1.94	1.95	1.96

Table V
Alternative Base Regressions For GDP Deflator with NAIRCU
DependentVariable: Change in Inflation As Measured by the GDP Chain Weighted Deflator
Unemployment Variable: Aggregate Unemployment rate 16 and Over
(19711-1998IV)

Regression No.	1	2	3	4	5	6
Quarterly Variance of NAIRU and NAIRCU	0.00	0.01	0.02	0.03	0.04	0.00
Constant NAIRU	6.30					
NAIRU 1998IV	6.30	6.47	6.52	6.53	6.52	
Constant NAIRCU	81.20					
NAIRCU 1998IV	81.20	81.58	81.84	82.04	82.21	81.20
Other Explanatory Variables (t-statistic)						
Constant	0.023	0.057	0.073	0.082	0.089	0.30
	(0.21)	(0.42)	(0.49)	(0.53)	(0.56)	(0.28)
Change in $Inf._{t-1}$	-0.261	-0.256	-0.255	-0.254	-0.253	-0.258
	(-3.20)	(-3.09)	(-3.06)	(-3.04)	(-3.03)	(-3.25)
Change in $Inf._{t-2}$	-0.401	-0.398	-0.397	-0.396	-0.396	-0.401
	(-4.64)	(-4.49	(-4.39)	(-4.36)	(-4.34)	(-4.59)
Unemploy. $Rate_t$	0.131	0.026	-0.012	-0.037	-0.053	
	(0.37)	(0.07)	(-0.03)	(-0.10)	(-0.15)	
Unemploy. $Rate_{t-1}$	0.002	0.048	0.066	0.079	0.086	
	(0.01)	(0.16)	(0.21)	(0.26)	(0.28)	
Cap. $Util._t$	0.187	0.166	0.159	0.154	0.151	0.148
	(3.57)	(3.04)	(2.85)	(2.73)	(2.64)	(4.96)
Log Likelihood	-156.96	-157.62	-157.93	-158.14	-158.31	-157.57
St. Error of Reg.	0.987	0.991	0.993	0.994	0.991	0.992
Durbin-Wat. Stat.	2.16	2.16	2.16	2.16	2.17	2.14

Table VI
Best Regression Result for Chain Weighted GDP Deflator
Dependent Variable: Change in Inflation As Measured by the Chain weighted GDP Deflator
Added Explanatory Variables: Change in Relative Price Shocks
(1971I-1998IV)

Quarterly Variability of NAIRCU	0.00
Constant NAIRCU	81.30
NAIRCU 1998IV	81.30
Other Explanatory Variables	
(t-statistics)	
Constant	0.014
	(0.166)
Change in Inflation$_{t-1}$	-0.463
	(-4.70)
Change in Inflation$_{t-2}$	-0.487
	(-5.33)
Change in Inflation$_{t-3}$	-0.293
	(-3.75)
Change in Inflation$_{t-4}$	-0.184
	(-2.78)
Percentage Change in Real Food and	0.451
Energy Prices$_t$ *	(4.27)
Percentage Change in Real Food and	-0.363
Energy Prices$_{t-1}$	(2.79)
Percentage Change in Real Food and	-0.256
Energy Prices$_{t-2}$	(-2.17)
Percentage Change in Real	-0.038
Import Prices$_t$**	(-3.82)
Percentage Change in Real	0.054
Import Prices$_{t-1}$	(3.69)
Percentage Change in Real	0.038
Import Prices$_{t-2}$	(3.06)
Gap between Inflation and	-0.045
Growth in Unit Labor Costs$_{t-1}$***	(-2.03)
Gap between Inflation and	-0.034
Growth in Unit Labor Costs$_{t-2}$	(-1.73)
Capacity Utilization	0.149
	(5.28)
Log Likelihood	-123.94
Adjusted R^2	.5615
St. Error of Regression	0.7822
Durbin-Watson Stat.****	2.09

* Real food and energy prices are defined as the overall chain weighted consumption price deflator divided by the chain weighted consumption less food and energy price deflator. This approach to measuring aggregate real food and energy prices has been used by Gordon in much of his empirical work.

** Real import prices are measured by the chain weighted price deflator for imports divided by the chain weighted GDP price deflator.

*** Inflation is measured by chain weighted GDP deflator and unit labor costs are BLS nonfarm unit labor costs.

**** No evidence of first order or higher serial correlation was evident from Breusch-Godfrey tests.

FIGURE 1: ESTIMATED NAIRUS

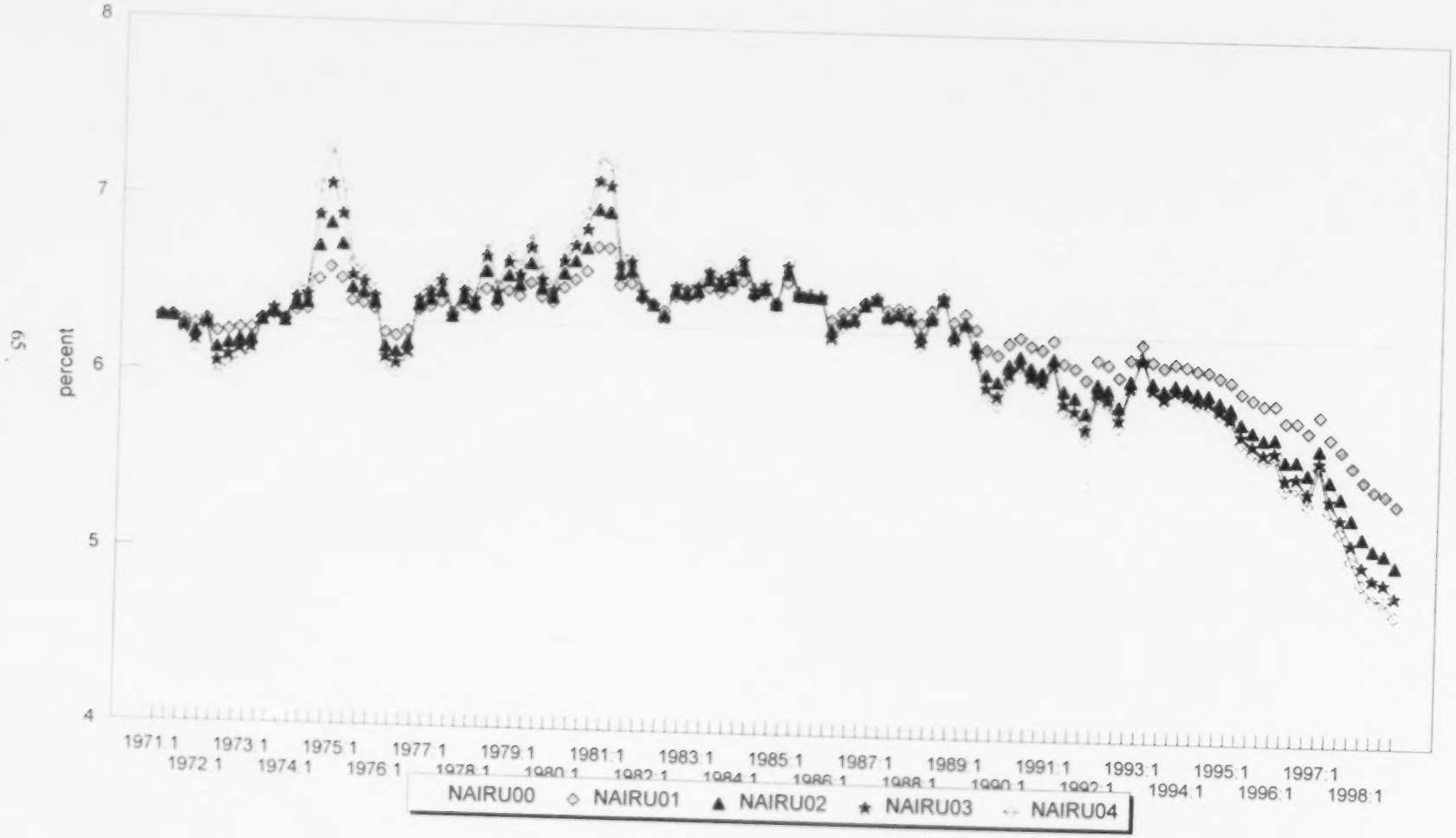
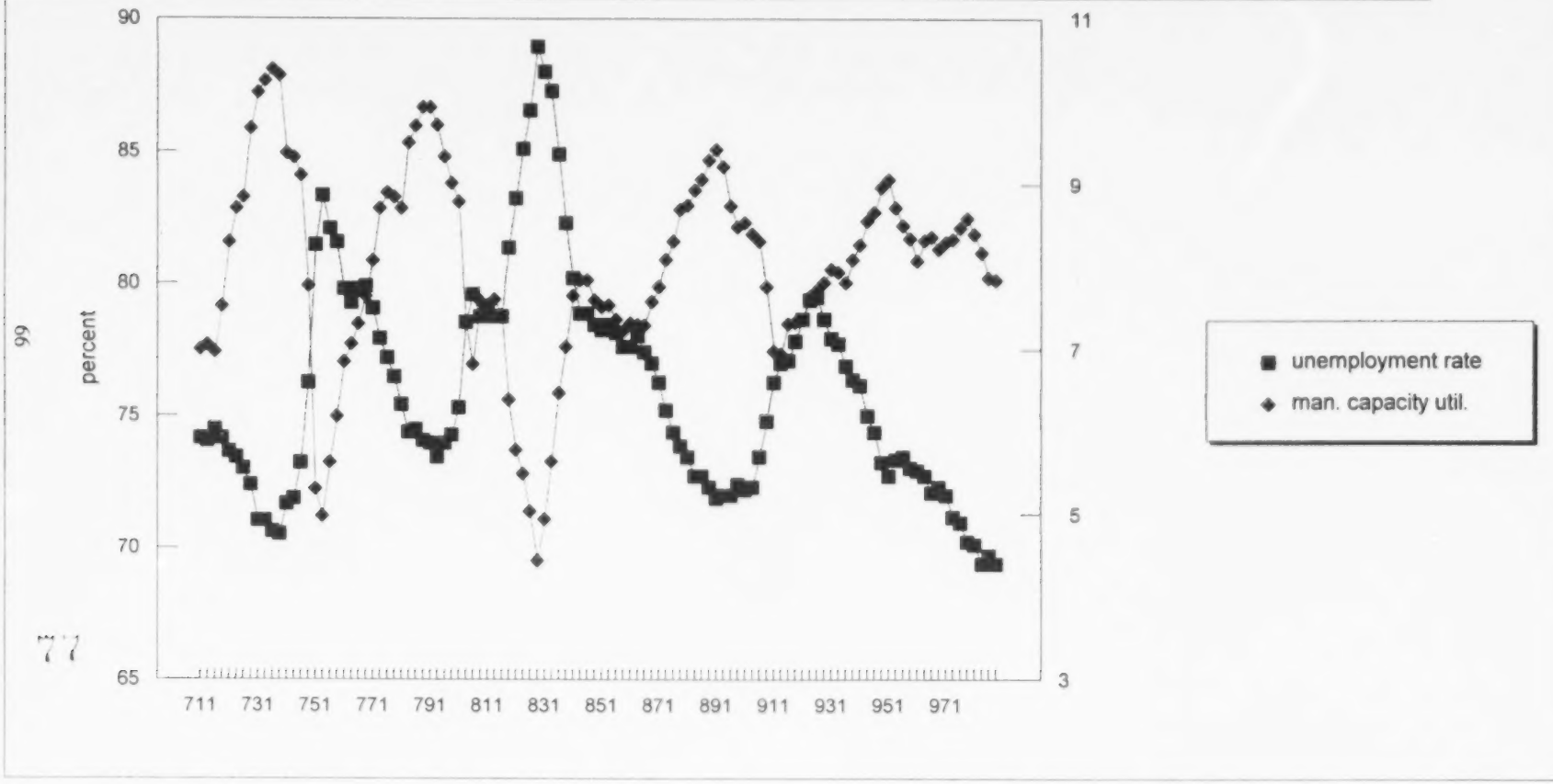
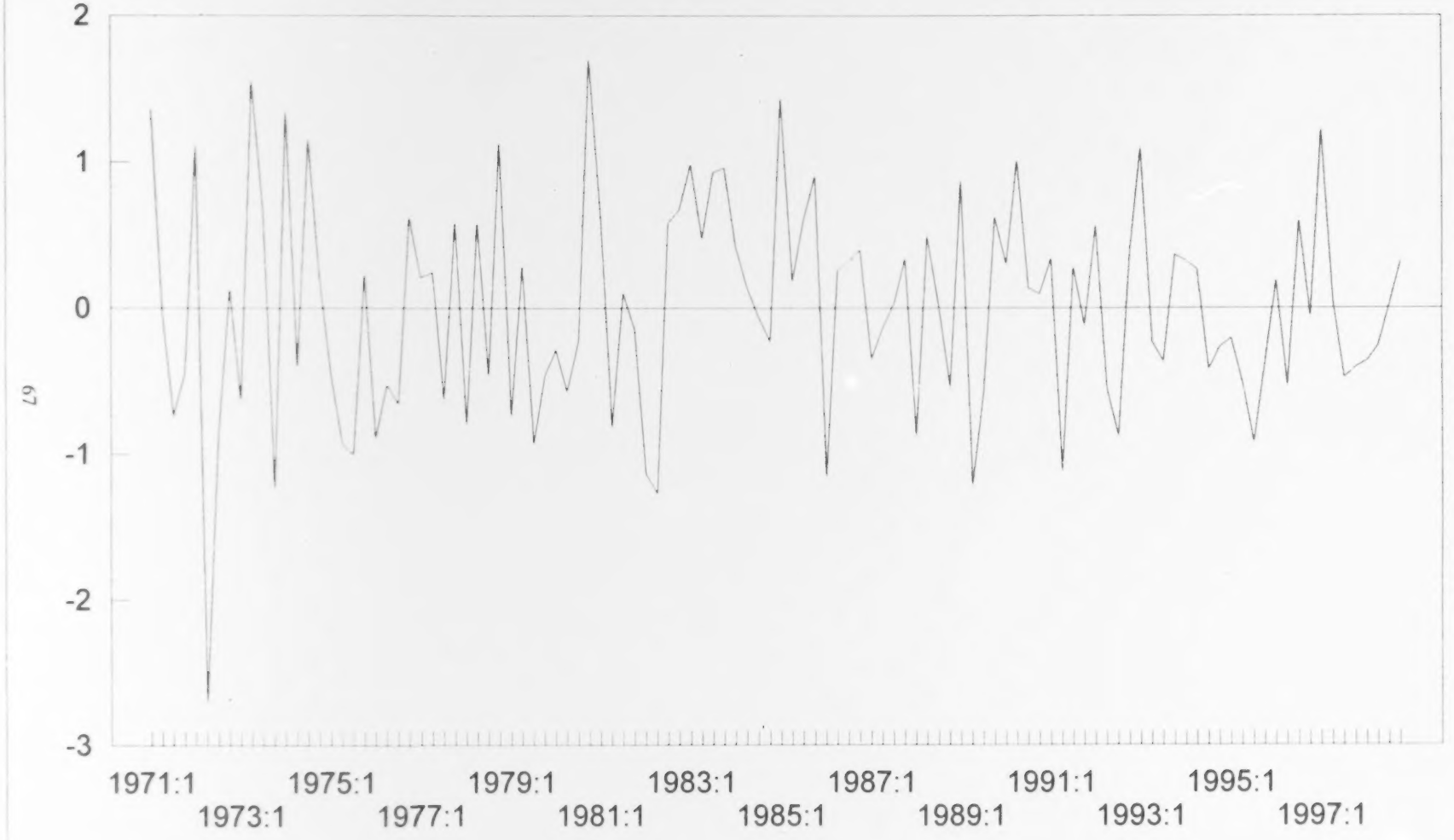


FIGURE 2: Capacity Utilization and the Unemployment Rate



Fiqure 3: Equation 3 Residuals



BUDGET FORECASTING FOR THE FOOD STAMP PROGRAM

Abstract

BUDGET FORECASTING FOR THE FOOD STAMP PROGRAM—Abstract

Chair: Kenneth Hanson
Economic Research Service, U.S. Department of Agriculture

Panelists:

Lisa Greenwood
Food and Consumer Services, U.S. Department of Agriculture

David Burr
Food and Consumer Services, U.S. Department of Agriculture

Edwin Lau
Office of Management and Budget

Valerie Baxter
Congressional Budget Office

Budget Forecasting for the Food Stamp Program

Chair: Kenneth Hanson
Economic Research Service, U.S. Department of Agriculture

Welfare Reform of 1996 dramatically changed the system of welfare programs supporting needy families and children. The Food Stamp Program (FSP) is one of a few social programs in the federal government that remain an entitlement, available on the basis of financial need. As an entitlement program, expenditures depend on economic conditions, and budget forecasts are the basis for requesting funds in the annual budget. In this session, analysts making the budget forecasts discuss their experience using econometric techniques in context of the institutional setting on the basis, timing, and use of these forecasts. Lisa Greenwood will describe the current budget forecasting procedure. Edwin Lau will describe the institutional setting under which the program agency forecasts its budget request. Valerie Baxter will discuss the issue of reconciling differences in budget forecasts which arise from differences in macroeconomic baselines used by Office of Management and Budget and Congressional Budget Office. David Burr will discuss problems that arise when unanticipated economic change causes unexpected program expenditures.

Panelists:

Lisa Greenwood
Food and Consumer Services, U.S. Department of Agriculture

David Burr
Food and Consumer Services, U.S. Department of Agriculture

Edwin Lau
Office of Management and Budget

Valerie Baxter
Congressional Budget Office

NEW DEVELOPMENT IN HEALTH MANPOWER FORECASTING

Chair: Emily DeCoster
Bureau of Health Professions
U. S. Department of Health and Human Services

Forecasting Workforce Demand: Physician Requirements and Health Service Demand (Abstract),
James M, Cultice, Bureau of Health Professions
U.S. Department of Health and Human Services

The Nursing Demand-Based Requirements Forecasting Model (NDBRFM),
Marshall S. Fritz, Bureau of Health Professions
U.S. Department of Health and Human Services

Forecasting Workforce Demand: Dental Personnel and Dentists,
Stuart Bernstein, Bureau of Health Professions
U.S. Department of Health and Human Services

Forecasting Workforce Demand: Physician Requirements and Health Service Demand

James M. Cultice, Bureau of Health Professions, U.S. Department of Health and Human Services

The Bureau of Health Professions' Integrated Requirements Model (IRM) forecasts requirements for 18 physician specialties, physician assistants, nurse practitioners, and selected other nonphysician clinicians per 100,000 people by assigning populations--by gender, age, and rural/urban location--to fee-for-service, staff HMO, IPA network, or uninsured delivery modes and applying practitioner staffing estimates by delivery mode. Practitioner requirements are modeled by delivery model for 1996 through 2020. Model users can analyze results of alternative policy scenarios by replacing baseline assumptions. In addition, the IRM produces reports summarizing the population by insurance status and urban/rural location, and a report on the practitioner staffing models association with the scenario being run.

THE NURSING DEMAND-BASED REQUIREMENTS FORECASTING MODEL (NDBRFM)

Marshall S. Fritz, Statistician[1]
Division of Nursing
Bureau of Health Professions, Health Resources and Services Administration, DHHS

Introduction

Legislation enacted in the 1970s requires the periodic submission of reports by the Secretary of the Department of Health and Human Services (DHHS) to the President and Congress on the numbers of health care personnel required to provide adequate health care for the Nation. The Health Resources and Services Administration (HRSA), through its Bureau of Health Professions (BHPr) component and the Division of Nursing within BHPr, developed conceptual frameworks and modeling structures for the projection of employment requirements of nursing personnel.

In its recent report the Institute of Medicine (IOM) [1] has noted recent changes regarding where nursing staff is being utilized, how they are being utilized, as well as what the relationships are between market-place changes, population demographics, and registered nurse training. Examples of health care sectors which have undergone recent changes impacting on nursing personnel requirements include inpatient hospital, ambulatory, and long term care services. Inpatient use of hospitals, and length of hospital stay, inpatient days, and the numbers of beds staffed have all declined. As the IOM noted, hospitals are restructuring, merging, and consolidating in order to maintain economic viability in the face of new market forces. Over the recent National Sample Surveys of Registered Nurses of 1992 [2] and 1996 [3], the numbers of nurses in hospital settings have remained stable while the percentage of all registered nurses (RN's) who work in hospital settings has dropped from over 66% to around 60%. Over the same period of time, nursing home, community public health, and ambulatory employment of registered nurses has increased. Nursing home settings employed 7% of RN's in 1992, increasing to 8.1% of RN's in 1996. Ambulatory settings increased their employment shares of RN's from 7.8% to 8.5% of all those employed over the same period. Within this restructuring to maintain economic viability, there have been changes in the relative balance and duties of nursing personnel of various levels of training.

At the same time that the economics of the provider institutions has changed, so are the demographics of the nation's population and the level of care that is being demanded undergoing change. Within 20 years, the large post-war baby boomer generation will begin to reach retirement age and will demand increasing levels of health care services compared to current overall levels of service demand by the elderly. According to the U.S. Bureau of the Census, Current Population Reports, P25-1130, Table No. 17, Resident Population Projections, there will be a large increase, both in absolute and relative terms, in the population over 55 years old by 2020. From 1998 to 2020, the total population will increase by about 20% while the percent of those who are over 55 will increase from about 21.1% to 29.4% of the general population. The projected growth of the oldest elderly subpopulation (for example, those over 85 of age will increase by about a third over this period) is likely to increase inpatient hospital and nursing home admissions at the same time that downsizing in hospitals is decreasing and internal shifting nursing personnel is occurring. According to IOM, while the overall rate of admissions is going down, the percent of those being admitted with high levels of acuity have increased.

Previous efforts to forecast requirements and supply of registered nurses used base year data from the period of the early 1990's, and did not account for the extensive structural changes in the health care delivery system. Nevertheless, these previous forecasting efforts did account for the aging of the population. Projections reported in the Basic Registered Nurse Workforce Report [4] suggest that even prior to incorporating market changes, the need to train and retain experienced registered nurses will become more pronounced as the year of 2020 is approached.

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[1] The views presented in this article are those of the author and do not necessarily represent the views of the Division of Nursing, the Bureau of Health Professions, Health Resources Services Administration, and the Department of Health and Human Services.

Table 1. Projections of RN Demand Requirements and Supply: 1995-2020

Year	Supply	Requirements	Requirement-Supply	Supply to Meet Demand
	(Millions)	(Millions)	(Millions)	(%)
(1)	(2)	(3)	(3)-(2)	[(3)-(2)]/(2)
1995	1.813	1.800	-0.013	-0.72%
2000	1.987	1.969	-0.018	-0.91%
2005	2.128	2.095	-0.033	-1.55%
2010	2.214	2.232	0.018	0.81%
2015	2.277	2.391	0.114	5.01%
2020	2.284	2.575	0.291	12.74%

Source: Projections by Division of Nursing, BHPr, HRSA,DHHS,1996

The forecasts plotted in **Figure 1** indicates that national staffing supply and demand requirements will remain approximately in balance until the year 2008. After 2008, an increasingly large difference between supply and requirement is anticipated. As shown in **Table 1**, consisting of sampled projections at five-year intervals, the percentage increase in supply necessary to keep pace with demand requirements will have to equal about 13% by the year 2020.

Given the IOM findings and the extensive changes in the dynamics of the health care system, updating the forecasting requirements model is imperative. This update will help ascertain how all these changes bear out in the net impact on the requirements for nursing personnel. The following sections briefly discuss (1) previous forecasting efforts, (2) the conceptual basis for the current requirement model, and (3) current efforts to enhance the current forecasting capabilities by including measures of market forces and upgrading the forecasting package platform.

Forecasting Demand for Nurses

Over the past two decades, a variety of modeling techniques have been used to forecast the requirements for RN's, LPN/LVN's (licensed practical/vocational nurses), and NA's (nursing aides/assistants). These techniques have included ratio estimating, expert judgment, system dynamics, historical trend analyses, and others. Some of these methods are no longer feasible because of lack of data, others because of the need for evidence-based decision processes. For example, trend analyses are no longer feasible because they relied on a number of since-discontinued, large-scale surveys.

The model is anticipated to accommodate sufficient detail about the variations that exist in the various health care delivery settings where nursing personnel are employed. Thirteen subsectors have been identified for the delivery of health care in these forecasting models, e.g., the short-term inpatient hospital. For the purpose of user application flexibility and ease of organizing outputs from the model forecasts, these subsectors are also aggregated in the forecasting package into higher-tier sectors comprised of related sectors, e.g., the hospital sector. The model is designed to produce: (1) estimates of quantified utilization and staffing demand requirements for each of the six sectors and thirteen subsectors **(Figure 2)**, (2) annual demand requirements of nurses for each State for each nursing occupation, and (3) annual demand of three nursing-related occupations, RNs, LPN/LVN's, and NA's, in all sectors and subsectors within each State.

The economics-based definition of requirements utilized here stands in contrast to other definitions of demand which are based on normative medical needs or theoretical staffing needs/desires. The requirement for nursing personnel is examined from the economic perspective of the number of full-time (FTE) staff that employers would actually hire in each subsector given prevailing economic market conditions, if not otherwise constrained by the availability of nursing personnel. This definition does not allow goal-based or normative-needs-based specifications/standards of nursing staffing requirements except to signify those levels of hiring from employers that would be required to meet consumer utilization rates for health care services.

For each subsector, there are units of productivity which typify the service provided in that sector. For example, in hospital subsectors, inpatient days are the measure of consumer utilization that is quantified and related to hospital nursing personnel requirements, while in the nonhospital ambulatory care subsector, visits are the measures of the consumer utilization. The model incorporates and quantifies specification of the important exogenous factors which are selected to reflect the underlying forces responsible for change in the health care system. For example, for the short-term inpatient hospital sector, one of the exogenous variables found to be significant for predicting inpatient RN requirements was the percentage of the total population covered by Medicaid; this variable was found to be negatively correlated to the rate that employers

would hire RN's for serving inpatient bed-days.

The current nursing demand requirements model is termed the Nursing Demand-Based Requirements Forecasting Model (NDBRFM) [5]. It is a two-stage multivariate model using cross-sectional data. The first stage determines the rate of utilization of health services by consumers using a General Services Demand Model (GSDM) [6], while the second stage combines the rate of workforce demand requirements per unit of service with the utilized numbers of units of service demanded by consumers. When multiplied together, while controlling for market factors, the resulting forecast represents the numbers of FTE's required to serve the forecasted utilization of health services by consumers.

The NDBRFM Mathematical Structure

The two-stage, nursing requirements forecasting model combines four multiplicative component factors (Equation 1). These multiplicative factors include per-capita utilization demand for health care services (first stage model), nursing requirements to deliver each service demanded (the second stage of the model), population estimates, and adjustments that control for the availability of nurses in the workforce. (The model assumes an equilibrium between supply and requirements at time zero.)

Separate equations are developed for each nursing occupation and health care subsector. In recent forecasting cycles, these utilization demand and nursing requirements relationships had been fitted to multivariate regression equations using weighted or unweighted ordinary least square algorithms. These equations are later applied with future, cross-sectional, variable value estimates at the state-level. National estimates for each subsector and nursing occupation (see Figure 2) are derived by summing the 51 individual State projections (the 50 States plus the District of Columbia).

The mathematical structure of the model can be expressed as shown in Equation (1) below. Equation (1) presents the four multiplicative factors which comprise the key components of the model structure for nursing requirements forecasting. These factors are parsed, or bracketed, into two pairs of subset products. Each bracketed expression is explained in this discussion of the mathematical structure to reflect the separate parts of the model which relate to consumer utilization of services and nursing workforce requirements to provide those services, respectively.

$$FTE_{NHS}(x_1(t),...x_m(t), v_1(t),...,v_n(t)) = [POP_{HS}(t) * PCD_{HS}(x_1(t),...x_m(t))] * [B_{NHS} * NRS_{NHS}(v_1(t),...,v_n(t))] \quad \text{Equation (1)}$$

where:

Overall Workforce Demand:

$FTE_{NHS}(x_1(t),...x_m(t), v_1(t),...,v_n(t)) =$

Workforce requirements for nursing occupation, N, in health care sector, H, in State, S. This is expressed in terms of the total FTE's at time, t, for a given State and where various exogenous, or independent, variables, $x_1(t),...x_m(t)$ and $v_1(t),...,v_n(t)$, impact upon the utilization of services (the PCD function) and nursing requirements for services (the NRS function). There may be different numbers of exogenous variables that best model utilization and nursing requirements, respectively.

Service Utilization (GSDM) Model Factors:

$POP_{HS}(t) =$

Population provided service by health care sector, H, in State, S, at time, t.

$PCD_{HS}(x_1(t),...x_m(t)) =$

The core generic function for the Per-Capita Demand (PCD) rates of utilization of health care services by consumers. It quantifies the demand- utilization-per-capita rates affected by independent variables, x_i, over time, t, in health sector, H, and in State, S. The independent variables, x_i, for each PCD equation have been selected to explain changes in service utilization rates in the base year. They have been selected from among many possible sets of variables relating to health care utilization by the population, including demographic, health care, geographic, and economic factors. The final set of variables for each equation were fit through the use of multivariate regression.

As mentioned above, the first bracketed expression within Equation (1),

$[POP_{HS}(t) * PCD_{HS}((x_1(t),...x_m(t))]$, represents the overall service utilization demanded by the population in State, S, and health care sector, H, at time, t.

Nursing Requirements (NDBRFM) Model Factors:

$B_{NHS} =$

Adjustment factor used to ensure that the regression equations applied to each of the 51 States will provide total within-sector estimates that match the base year RN staffing figures in that sector, H, and State, S. The base year is typically the year in which the National Sample Survey of RN's was last undertaken.

Rationale for this adjustment is that the utilization of services is in equilibrium in the base year. The economic requirement of the conceptual framework is that employers would hire that number of nurses deemed appropriate to serve the utilization demanded, and paid for, by consumers.

These adjustments are treated in the model as being constant over time from the base year forward. By being constant over time, it is hypothesized that the unique affects within each State do not vary into the future. Thus, the changes over time in each State are hypothesized to be due to the exogenous variables

values.

For most of subsector settings, actual State data for RN workforce distribution is available, not just national averages. Data is sparse regarding LPN/LVN's and NA's in the various subsectors in which they are employed, more so than has been true for RN's. In these situations with insufficient or unavailable State-level data for that subsector, the value of adjustment factor at the base year takes on a different meaning; actual observations are synthetically estimated using the national overall average rate.

$NRS_{N,H,S}(v_1(t),....,v_m(t)) =$
The core generic function for the rates of nursing requirements for service, i.e., workforce demand. It quantifies the FTE workforce-utilization-per-service rates affected by independent variables, v_m over time, t, in health sector, H, and in State, S, and for nursing occupation, N. The independent variables, v_m for each NRS equation have been selected to explain changes in requirements rates in the base year and to be applicable at a future time, t. They have been selected from among many possible sets of variables relating to demand for nurse providers of services including demographic, health care, geographic, and economic factors. The final set of variables for each equation were fit through the use of multivariate regression.

As mentioned above, the second bracketed expression within Equation 1,
$[B_{N,H,S} * NRS_{N,H,S}(v_1(t),....,v_m(t))]$, represents the demand rate for nurses, after adjustment, in nursing occupation, N, State, S, and health care sector, H, per unit of utilized service at time, t.

The selections of correlates (independent variables) for inclusion in the model must satisfy statistical and substantive requirements. The statistical requirement is that the variables must be independent but identically distributed (i.i.d.). The substantive requirements is that these variables are substantially related to the quantities modeled, and explain the greatest amount of the variations in demand for nurses.

Data Sources Used for Forecasting

Much of the data used in the forecasting phases, including the state-level cross-sectional data, come from national surveys conducted by: the Bureau of the Census, the Bureau of Economic Analysis, the National Center for Health Statistics, the Health Resources and Services Administration, and the American Hospital Association. Some of the surveys have reported state-level information. However, some of the surveys were not able to encompass sample sizes sufficient to allow conclusions for each of the 51 States. In the latter instances, national averages have been used as default proxies for State data where disaggregate state-level estimates have not been available directly from the survey databases or reports.

Example: Forecasting RN FTE's per 1000 Inpatient Hospital Days.

As discussed above, the mathematical structure of the forecasting model consists of a number of discrete equations which have been fit with statistically significant variables, using multivariate regression. An example from the set of forecasting equations from the last forecasting application cycle is presented in Equation (2) below. Equation (2) provides the multivariate regression equation that was fit to predict the rate of requirements for RN's (RN FTE rate) per 1,000 short-term hospital bed-days:

RN FTE'S PER 1,000 INPATIENT HOSPITAL DAYS (SSTND) = Equation (2):

6.2190 (Constant Term) +

-15.7005 * the Percentage of the Total Population covered by Medicaid (PMCAID) +

1.9937 * the Managed Care Saturation Index (MCNDX) +

-2.1925 * the # of Long-Term Hospital Inpatient Days Per Capita (LTDYTP) +

2.5822 * Short Term Hospital Outpatient Visits Per Capita (STEVP)

RN FTE's rate per 1,000 inpatient hospital days was found to be statistically related to four factors: Medicaid coverage prevalence, managed care predominance, inpatient day utilization rate, and outpatient visit utilization rate. The relationship between the relative size of the Medicaid-eligible population can be used to understand how the numbers of inpatient staff FTE's would vary with changes in increases or decreases in Medicaid predominance in a given State. Equation (2) infers that employers would reduce staffing rates in response to an increase in the Medicaid-eligible predominance in a State, all other variables being kept constant. Should the percentage of those covered by Medicaid increase by a full percentage point from the base model, the equation projects that the rate of RN's per thousand bed-days would decrease by approximately 0.16 FTE's per thousand bed-days over the rate obtained from the baseline data. Such a relationship is commensurate with the economic rationalizations that Medicaid reimbursement rates are lower than other open market reimbursement schedules and that lower average provider income per patient would lead employers to reduce staffing in response.

To determine the total FTE requirements, or the change in the respective FTE requirements, the rate of RN's per thousand

bed-days, the dependent variable in the above example, must be multiplied by the numbers of thousands of inpatient bed-days in the appropriate year for a population in each respective State.

Enhancing the Forecasting Model

The current model is undergoing several major enhancements: (1) update of the base year data and enhancing the quality of data input by using data mining; (2) inclusion of exogenous (independent) variables that will attempt to capture changes in the health care market that might affect recruitment of nurses; and (3) enhancement of the computer software to make it more flexible and user friendly.

Data: Updates and Enhancement

The previous NDBRFM and GSDM model applications used survey estimates from the early 1990's. The current update will use survey data stemming from the mid-1990's for its equation fitting. The updated data base contains market-based information for the base year, i.e., nursing staffing levels employers actually hired to provide the care demanded and utilized by consumers, along with other socioeconomic, socio-demographic, and health care information.

Selection of Exogenous Variables

The types of exogenous variables that are conceptually considered to assess the impact on demand include the following categories:

- health status indicators (i.e., mortality vital events, morbidity indicators)
- demographic characteristics of the population (i.e., age, race, sex, rural/urban)
- economic status of the population (i.e., per-capita income or cost of living measures, trends of employment in key industries/occupations with or without educational attainment, unemployment rates)
- insurance status for the population (i.e., levels of public/private health insurance, and managed care coverage)
- health care sector productivity/outputs.

Figure 3 consists of a table displaying the selected exogenous variables from the 1996 equation fitting for inpatient short-term hospital. A separate column appears on the right hand side of the table which displays a tentative set of exogenous variables being examined in the cycle currently under way. Variables currently being considered for use as exogenous variables in the new equation fitting efforts for inpatient sector bed-day utilization demand per capita and inpatient sector FTE demand per bed-day in each state include:

1. the ratio of actual-to-expected deaths
2. the degree of managed care penetration per capita income
3. geographic effects of State or region
4. within the country, and
5. percent of the population covered by Medicaid or Medicare

Since the requirements model forecasts both at the state level and at the national level, two enhancements being sought are: (1) the incorporation of State- and regional-specific affects to improve the ability to account for unique differences at the State level, and (2) alternatives for a national model beyond arithmetic aggregation of state-level estimates to national-level estimates.

The inferred impacts on utilization or staffing requirements that particular States or geographic regions may have, in terms of their unique delivery systems, unique socioeconomic conditions, or unique socio-demographic circumstances, were not extensively reviewed in earlier model calibrations. Examination is planned to determine if judicious use of these geographic-specific affects will add significantly to the reliability of the models. For example, in the previous equation fitting application for the GSDM model, Florida was found to have a significant difference in home health care utilization rates for the elderly compared with essentially all other States, and a particular Florida-effect was incorporated into the predictive model.

National estimates have been obtained by aggregating state-level estimates without accounting for State differentials in size, composition, distribution of health care needs. Among the options to enhance the national estimate is a weighting strategy. Among the weighting options being considered for the current model update are weighting adjustments based on population size or other health-care-related index which reflect rates or absolute magnitudes and which are of relevance to each discrete dependent variable within each equation and subsector.

The NDBRFM Computer Model and User Interface

Software Update: Using a WINDOWS-Based Environment. Previous versions of the forecasting model were written in software code that would work in the DOS environment. Advances in hardware and software have allowed for evolutionary improvements in the user-interface of a WINDOWS-Based environment. It is anticipated that the upgraded environment will allow the user greater ease in choosing among the various sectors to forecast and in aggregating results over these sectors for a well-managed series of runs and output reports. A common interface is being developed for the service utilization (GSDM) and nursing requirements (NDBRFM) components.

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User Flexibility in Developing Alternate Scenarios

The model forecasting computer software allows the users to conduct "what-if" inquiries. The user has the flexibility to extend the alternative scenarios to one or more forecasting variables, to one or more individual states, and/or to one or more future years. Consequently, all exogenous variables which are included in the model must be amenable to future forecast to the outer limits of the time period for which the model is to be applied, not just to be applied solely in the base year for which the calibration is undertaken. Currently, the forecasting package has been designed to accommodate forecasts to the year 2020 and all input variables in current applications must have baseline forecasts to the year 2020.

As mentioned above, national forecasts are obtained through aggregation of State forecasts. To implement an alternate scenario for the whole country, the values of one or more input variables would need to be updated by the user for all States. For example, suppose that the user wants to forecast the impact that a new medical technology would have that would lower death rates by 20% in all States. Referring to **Equation (2)**, for the short-term inpatient hospital RN subsector, the user can selectively vary one or more of the exogenous, input variables. In this example, the user could manually recalculate the death-rate default values downward by 20% for the years of 2006 to 2020 in the input file. The user can estimate the net impact on staffing of the alternative scenario by performing two runs of the package -- one using the default values and the other using the user's modified scenario -- and then compare the national totals from each run.

Future Challenges, Research, Assessments, and Data Needs

Modeling the dynamics of modes of health care delivery. There is a continuing need to model the changing structure and dynamics of managed care. It is not a one-dimensional phenomenon. Managed care takes on many flavors of structure and administration, with varying degrees of impacts on utilization and demand.

Need for enhanced State-level data. In certain subsectors, there is a lack of State level data. This is true even for RN's. As a result of this lack of reliable data uniformly available for all States, the previous models have defaulted to national average rates for the ambulatory, public health, and home health subsectors, among others. In several subsectors, there is no known source for actual nurse-to-service utilization ratios, as well as being based on reliable data for each State. This less-than-ideal condition reduces the robustness of the model to accommodate actual, unique variation in levels of service among the States. Proposed methods for improving model specificity and robustness include data mining measures, such as variance shrinkage estimators and other small area estimation techniques.

Maximizing Model Utility and Reliability in Being Capable of Forecasting on Both the State and National Level. There are dual objectives of constructing forecasting models which are highly robust when applied for national projections, as well as when applied for individual State projections. The lack of available, rich sources of data has restricted such an approach. As a result of these past limitations, the national forecast estimates have been developed as summations of the individual State forecasts. Even at the State level, only one observation per State has been available for the base year calibration.

For each of these challenges for research and data involving state modeling, national modeling, and the affects of managed care on the health care delivery system, the current enhancement work on the model has examined alternative approaches. Continuing research is desirable on alternatives for model improvements and the resulting reliability of both the State and national estimates from these alternatives.

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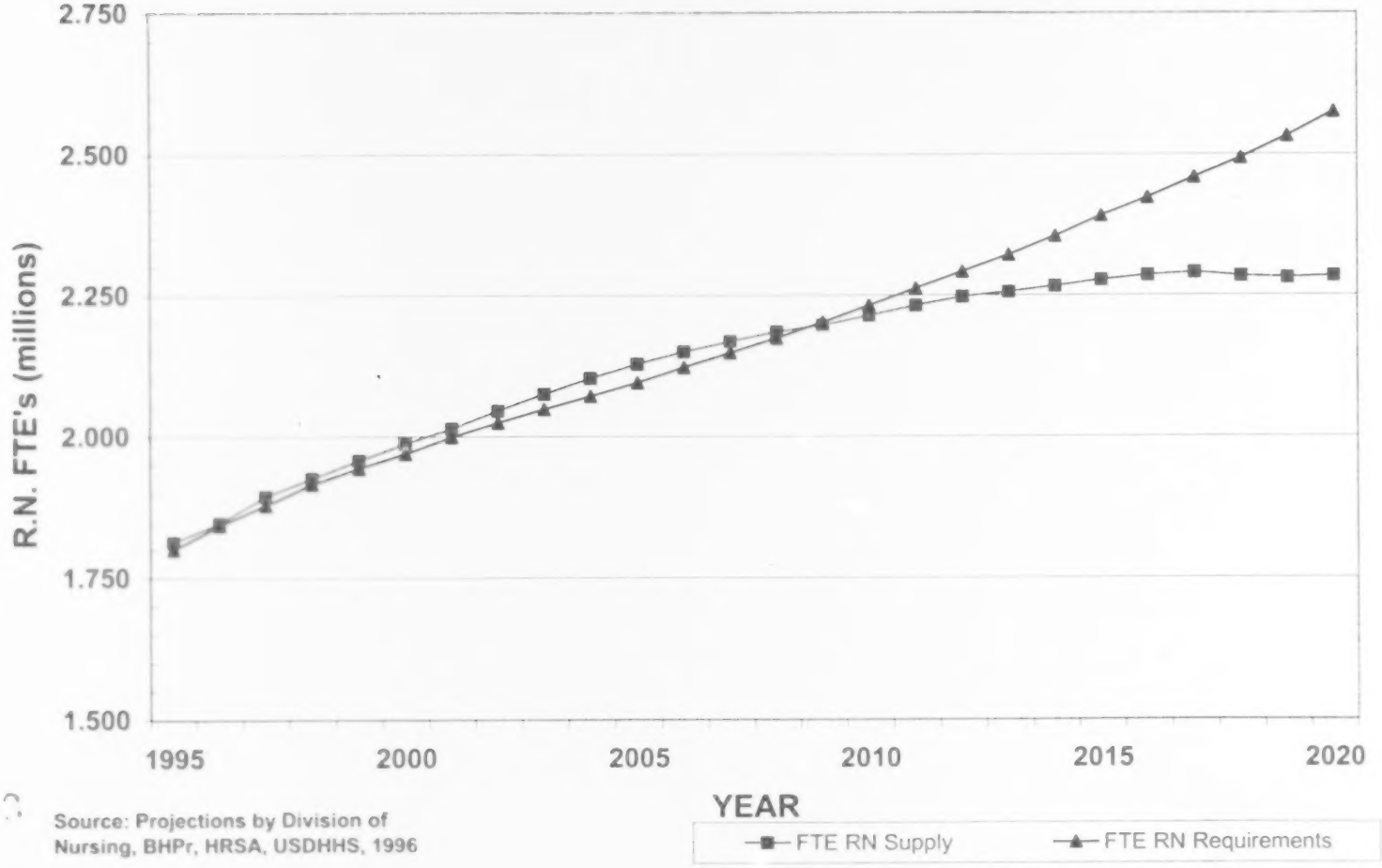
FIGURE 1

PROJECTIONS OF FTE SUPPLY AND DEMAND REQUIREMENTS FOR R.N.'s
Estimates as of December 31, 1995-2020



Source: Projections by Division of Nursing, BHPr, HRSA, USDHHS, 1996

Figure 2

NDBRFM Health Care Service Sectors/Subsectors & Applicability to Each Nursing-Related Occupation

Sectors & Subsectors	Applicable Nursing Occupation		
Sector: Hospital			
1. Short-Term Hospital Inpatient	RN	LPN	NA
2. Short-Term Hospital Outpatient (non-ER) Dept	RN		
3. Short-Term Hospital ER	RN		
4. Long-Term/Psych/Other Hospital	RN	LPN	NA
Sector: Nursing Homes			
5. Nursing Homes	RN	LPN	
6. Board & Care Homes	RN		
Sector: Ambulatory Non-Hospital			
7. Ambulatory Care (non-institutional)	RN		
Sector: Public and Community Health			
8. Home Health Care	RN	LPN	NA
9. Occupational Health Care	RN		
10. School Health	RN		
11. Public Health	RN		
Sector: Education			
12. Nursing Education Programs	RN		
Sector: Other			
13. Other Nursing Employment	RN		

This table lists the types of nursing occupations which have expectations of being used by employers in each of the sectors and subsectors shown above. Due to the unavailability of data, the utilization of nursing personnel cannot be quantified in a limited number of these sectors.

Figure 3

COMPARISON BETWEEN PAST SIGNIFICANT EXOGENOUS VARIABLES AND PROPOSED SET OF EXOGENOUS VARIABLES FOR THE CURRENT CYCLE --

FOR SHORT-TERM INPATIENT HOSPITAL DEMAND REGRESSION MODELS

Dependent Variable	Past Exogenous Variables	Proposed Exogenous Variables
	GSDM Forecasts of Bed Days per 1,000 Population	
Short-Term Hospital Inpatient Days per 1, 000 for <65 pop.	Actual/Expected deaths % Uninsured HMO Penetration	Actual/Expected deaths % Uninsured HMO Penetration Per Capita Income Region % Population rural
Short-Term Hospital Inpatient Days per 1, 000 for >65 pop.	Actual/Expected deaths Per Capita Income HMO Penetration	Actual/Expected deaths HMO Penetration Per Capita Income Region % Population rural
	NDBRFM Forecasts of RN's per 1,000 Inpatient Bed Days	
Short-Term Hospital Inpatient RN's per 1,000 Bed Days	% Covered by Medicaid HMO Penetration Per Capita Long-Term Hospital Inpatient Days Outpatient Visits per Capita	% rural Median Income Death rates HMO Penetration Region % Covered by Medicaid % Covered by Medicare
	NDBRFM Forecasts of LPN's per 1,000 Inpatient Bed Days	
Short-Term Hospital Inpatient RN's per 1,000 Bed Days	National & State Ins. Coverage HMO Penetration Per Capita Long-Term Hospital Inpatient Days NA's per 1,000 Short-Term Inpatient Days	% rural Median Income Death rates HMO Penetration
	NDBRFM Forecasts of NA's per 1,000 Inpatient Bed Days	
Short-Term Hospital Inpatient RN's per 1,000 Bed Days	% of Short-Term Days for >65's Actual/Expected deaths for <65's	% rural Median Income Death rates HMO Penetration

FORECASTING WORKFORCE SUPPLY: DENTAL PERSONNEL AND DENTISTS

Stuart Bernstein
Bureau of Health Professions

The Bureau of Health Professions, Health Resources and Services Administration, a component of the U.S. Public Health Service, has the principal federal responsibility for assessing the status of the nation's supply of health personnel. While health manpower planning has been an important function of the Bureau and its predecessor agencies for many years, it was not until the passage of the Health Professions Educational Assistance Act of 1976 (PL 94-484), specifically section 708 of the Act, that the Secretary of the Department of Health and Human services was required to establish a program to collect, analyze and disseminate data on the status of health personnel. Section 708 also contained an important provision mandating periodic reports to the President and Congress. The reports served as an important source of information on the national level, for state and local governments, health professions educational institutions, and health professional associations. To date, a total of eight reports to the President and Congress on the Status of Health personnel have been published.

The dental sections of the Reports contained information on the current status of dental personnel, trends in dentist supply, educational trends and estimates of future supply. Over the years, a clear distinction has been drawn between projecting supply and forecasting requirements for dentists. For dental requirements forecasting, the Bureau has used the Econometric Model of the Dental Sector which provided forecasts of dental employment and utilization using alternative economic scenarios. Supply projections have consisted of ranges of estimates reflecting the most likely levels of dentists over the projection period under alternative sets of assumptions. Such projections reflected the influence of rates of entry into the profession and retirement, separation and mortality rates on the stock of dentists. The supply model when compared with actual numbers of active dentists obtained from the American Dental Association has proven to be highly accurate. In a moment, I will delineate this level of accuracy of estimates and projections contained in the first eight reports to Congress.

Basically, the Model starts with the base of active dentists from the American Dental Association. This Base is defined by gender and by age from 24 to age 75. Each year, dental school graduates are added to the active pool of dentists, and a proportion of active dentists are separated out by individual age and gender. These separations are due to retirement and mortality. Such rates are obtained from the Bureau of Labor Statistics and the National Center for Health Statistics respectively and reflect the experience of white males and physicians as a proxy for dentists, which no specific data are available. Another component which the Model considers are lag factors. These factors relate to what proportion of dental school graduates go into active practice immediately after graduation or delay their entry by one or more years. The primary reason for this delay or lag is entry into dental residency programs.

This supply forecasting model, with some minor variations, has been utilized in generating projections in eight reports to the president and Congress. The Model had been programmed for the NIH Computer System, but has recently been programmed to run on the PC utilizing Quattro Pro. During the period encompassed by the eight reports to Congress, the dental health sector experienced significant changes in the organization and financing of dental services, practice productivity, technology of dental treatment, disease patterns and levels of dental personnel. The differing assumptions underlying the projections over time have considered these changes.

Because of the uncertainties about future first year enrollment data, the Bureau used three different projection levels for the supply of active dentists, a low or pessimistic level, a basic or more likely level, and a high or optimistic level. Each projection level was based on different assumptions about how many new graduates - estimated from first-year enrollment levels after accounting for student attrition - would enter the profession annually over the projection period. Assumptions on first-year enrollments were based upon economic and demographic factors that in the past had influenced the size of the applicant pools, dental school class sizes, first-year student trends, as well as other factors. Dental supply projections using the basic or most likely assumptions were used for the following retrospective analysis in which the projections of active dentists over time in the various reports to Congress

were compared with actual American Dental Association data. Such an analysis demonstrates the historical validity of the dentist supply projection model.

Short-Range Projections: 1980 and 1985

The 1980 and 1985 projections have tracked very well. The 1980 projection of 126,240, published in 1978 and probably calculated in 1976 using a pre-1976 baseline figure, is virtually equal to the 126,200 actual. The range of 140,740 through 141,500 projections for 1985 presented in the 1978 through 1986 Reports are excellent, with an actual of 140,700.

Mid-Range Projections: 1990

The 1990 actual of 152,000 is an interpolation based on the ADA's 1991 census figure. The 1978 through 1990 projections range from 149,700 through 154,760. The three earliest projections–done in 1978, 1980 and 1982--are about 2,000 dentists too high; the 1984 and 1986 are closer–within 700 to 1,200; the most recent in 1988–are about 2,000 too low.

Long-Range Projections

The Third Report was the first to include projections for years 1995 and 2000. Projections for the year 1995 in these reports range from 152,000 to 157,000, extremely close to the 1995 ADA actual of 153,300.

A new 1995 database of 153,300 active dentists has recently been entered into the Model. Utilizing this new database, a series of projections have been run using three different assumptions. A basic series assumes the continuation of average growth in first year enrollments observed between 1989 and 1997 of 1.03 annually to the year 2002 . The Model then assumes continuation of the 2002 level to the end of the projection period. A low series assumes maintenance of existing fist year enrollment from 1997 to the end of the projection period. A high series assumes a 1.3 percent annual increase of first year enrollment from 1998 to 2007. This assumption reflects the annual increase in dental enrollment only during the most recent years. The following results of the updated projections are using only the basic series. In this series, the numbers of active dentists are projected to increase from 153,300 in 1995 to 160,500 in the year 2000 and to 170,500 in the year 2010. A further increase to 171,700 in 2015 is projected; however there will be a decline in the number to 170,100 by the year 2020. This decline is due to the fact that an insufficient number of new dentists are expected to enter the active pool to balance the number of dentists leaving the profession by that year. The ratio of active dentists to 100,000 population is projected to decline beginning at the turn of the century. This ratio will decline from 58.4 in the year 2000 to 57.3 in 2010 and further decline to 52.7 in 2020, a difference of more than 10 percent from the 1995 level.

Summary of Future Directions

A number of critical activities are now ongoing to improve the accuracy of forecasts of dentists. The Model was recently reprogrammed to allow for separate entry of foreign trained dentists coming into the United States. Data will be forthcoming from the American Dental Association which will provide input on the behavior of these students as to whether they remain in the US for practice. Other data forthcoming will permit us to improve the accuracy of lag factors in the model by providing information on residency patterns.

However, the most critical information needed for the Model relates to the behavior of young female dentists. The numbers of women in dentistry have been increasing substantially as more than a third of enrollees are now female. New data are needed to permit us to incorporate the impact of increased proportion of women on workforce patterns. Such data will permit us to determine full time equivalencies for active dentists which will be particularly important if it is found that women dentists work fewer hours than their male counterparts. Another area in which input rates need to be modified is mortality rates. Such rates need to be updated to be gender specific. In addition, if the model is to forecast by race/ethnicity, mortality and retirement rates need to be developed by race/ethnic status. Similarly, retirements patterns of active dentists need to be better incorporated into the Model. This is particularly critical in relation to the increasing number of younger female dentists. The model needs to incorporate data on temporary movement out of the active pool which will become more relevant as women dentists take on work patterns demonstrated in other professions.

FORECASTING AGRICULTURAL COMMODITY PRICES

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Providing Timely Farm Forecasts: Using Wheat Futures Prices to Forecast U.S. Wheat Prices at the Farm Level,
Linwood A. Hoffman, Economic Research Service, U.S. Department of Agriculture
Joseph Balagtas, University of California, Davis

Market Analysis and U.S. Cotton Prices,
Leslie A. Meyer, Economic Research Service, U.S. Department of Agriculture

Production and Price Impacts of U.S. Crop Insurance Subsidies: Some Preliminary Results,
C. Edwin Young, William W. Lin. Jerry R. Skees, and Randall Schnepf,
Economic Research Service, U.S. Department of Agriculture

Providing Timely Farm Price Forecasts: Using Wheat Futures Prices To Forecast U.S. Wheat Prices at the Farm Level

Linwood A. Hoffman, U.S. Department of Agriculture, Economic Research Service and Joseph Balagtas, University of California, Davis

Introduction

Information regarding wheat prices is critical to market participants making production and marketing decisions, in part, to manage price risk. Market information is also important to policy analysts who have to assess the impacts of domestic and international events upon wheat farm prices. Price information has become even more important partly because of changes in U.S. agricultural policy. Passage of The Federal Agriculture Improvement and Reform Act of 1996 (1996 Farm Act) continues the sector's trend toward market orientation and transfers risk from the government to the private sector.

The U.S. Department of Agriculture analyzes agricultural commodity markets on a monthly basis and publishes current year market information, including price projections (except cotton). Due to policy changes and an increased desire to manage price and income risks, the need for reliable price projection models is paramount. Although USDA revised several quantitative price forecasting models to account for changes in policy (Westcott and Hoffman; Childs and Westcott; and Meyer), other procedures that use futures prices also offer opportunities for commodity price forecasting (Hoffman).

Futures prices are determined by the interaction of the expected supply and demand for a commodity. They are considered a composite indicator of expected supply and use and thus can be used to forecast short-run farm prices (Danthine; Gardner; Peck; and Rausser and Just). Hedgers and speculators evaluate a number of factors, including, but not limited to planting intentions, weather, production forecasts, government policies, and the potential for domestic or export consumption. Hedgers deal with the actual commodity, as well as with futures contracts. Frequently, speculators have no direct connection to the cash commodity, but expect to profit from changes in futures prices.

In a recent article, Tomek has summarized the literature on the use of futures prices as a price level forecast. He states that, "futures prices can be viewed as forecasts of maturity-month prices and the evidence suggests that it is difficult for structural or time-series econometric models to improve on forecasts futures markets provide." However, he mentions that accuracy of a futures forecast can decline rapidly for forecasts made more than three or four months in advance. The reason for such a situation is the availability of information, which can change significantly over time, thereby changing price forecasts. Consequently, the development of accurate price forecasts is a challenge especially for a more distant time. Thus, even if a futures price is an unbiased forecast, a large variance of forecast error may occur.

The question then becomes how can we convert the information present in futures prices into useful specific cash price forecasts—particularly for a crop year or other designated time period. Most market participants understand that current futures prices provide important information about cash prices on future dates. However, these participants need to be able to forecast a cash price at a location and time when they plan to buy or sell. Thus, they need to predict the basis, which is the difference between the local cash price and the observed futures price. Similarly, policy analysts and commodity forecasters who are forecasting the U.S. season-average price need to be able to predict the monthly basis between the national producer cash price and nearby futures price. Monthly U.S. cash price forecasts are then weighted and summed into a season-average price forecast.

The objective of this paper is to construct a model that uses futures prices to provide timely and reliable forecasts of season-average prices received by farmers throughout the crop year. Wheat futures prices are used to forecast the season-average price received by farmers for U.S. wheat. Forecasts are presented for crop years 1986 through 1999 along with a forecast accuracy test. A comparison of the futures model price forecast is made with the mid-point of USDA's monthly price projection released in World Agricultural Supply and Demand Estimates (WASDE). The effects that different bases or marketing weights have upon the price forecasts are analyzed.

Forecast Framework

This section explains the forecasting model and its various components such as futures prices, basis, and marketing weights. Next, the sequential steps taken to provide futures forecasts are outlined and explained.

A season-average wheat price forecast is computed from five futures price contracts traded throughout the crop year. The forecast period covers 13 months, beginning in May, one month before the crop year begins and concludes the following May, the last month of the crop year. Initially, each month's forecast is based on a futures price and a weighted season-average price forecast is derived. Then, if an actual cash price exists for the month, it is used instead of the forecast. Consequently, the season-average price would then be a composite of actual and forecasted prices. As we move closer to the end of the marketing year there are more months with actual cash prices and fewer months with forecasted prices. Thus, the forecast error of the season-average price will decline as we move closer to the end of the crop year.

Forecast Model

The forecast of the weighted season-average farm price (SAP) is computed as:

$$SAP_m = \sum_{i=1}^{m-1} W_i P_i + \sum_{i=m}^{12} W_i (F_{mk} + B_{ik})$$

where:

SAP_m = forecast of the season average price made in month m.

W_i = weight for month i.

P_i = actual price in month i.

F_{mk} = observed price in month m for futures that matures in month k.

B_{ik} = expected basis, which is equal to cash price in month i minus futures price in month i that matures in month k. This basis is usually a negative number.

m = 0, 1, 2, ... 12, month during which forecast is made.

i = month forecasted.

k = first futures maturing after month forecasted.

Basis

The difference between a cash price at a specific location and the price of the nearby futures contract is known as the basis. The basis tends to be more stable or predictable than either the cash price or futures price. Several factors affect the basis and help explain why the basis varies from one location to another. Some specific factors include: local supply and demand conditions for the commodity and its substitutes, transportation and handling charges, transportation bottlenecks, availability of storage space, storage costs, conditioning capacities, and market expectations. The basis computed for this analysis reflects a composite of these factors because it represents an average of U.S. conditions.

The basis used in this study is the arithmetic difference between the monthly U.S. average cash wheat price received by producers, for example in June, and a monthly average of the nearby futures settlement prices observed during June. For example, the June basis is the difference between the June-average cash price received by producers and June's average settlement price of the July futures contract. A 5-year moving average basis is used in this analysis to provide a representative basis. The basis is updated at the end of each crop year.

The effects of a different basis estimate on price forecasts are analyzed. A recent crop year, 1996/97, was selected to perform this analysis. It was selected because it had a large forecast error, relative to other crop years, that occurred in a year of declining prices. Would a more accurate basis estimate reduce this forecast error? The revised basis pattern, an average of bases for crop years 1989 and 1991, uses a basis that is similar to the observed pattern in the beginning of the 1996/97 crop year.

Exploring alternative basis forecasting methods could improve futures price forecasts. For example, Jiang and Hayenga found that a 3- year average basis model that included market information and a seasonal ARIMA basis model provided a better basis forecast than a simple 3-year average basis model. Tomek discusses two types of basis

forecasting models. The first one relates to bases involved with inventories carried into the next year and the second one relates to bases involved with intrayear inventories.

Monthly Weights

Monthly marketings are used to construct the weighted season-average price. Each month's weight represents the proportion of the year's crop marketed in that month. A 5-year moving average of these monthly weights is constructed and is updated annually after the release of USDA's December issue of Crop Production. Beginning in 1998 the marketing weights are published in the September Agricultural Prices report. The monthly prices, actual or forecast, are multiplied by each month's corresponding weight.

If the analyst has better information than a 5-year average, this data should be used. Perfect knowledge of marketing weights will be assumed as an alternative to assess these effects on the price forecast.

Data

Historical daily settlement prices are obtained from the Commodity Futures Trading Commission for each contract traded on the Kansas City Board of Trade for crop years 1981 through 1994. Futures prices for more recent years were obtained from Technical Tools Inc. Cash prices are from Agricultural Prices, published by USDA's National Agricultural Statistics Service. U. S. Department of Agriculture price projections are from World Supply and Demand Estimates, published by USDA's World Agricultural Outlook Board. Weights for monthly marketings are from various issues of USDA's December Crop Production. Beginning in 1998, monthly marketing weights are published in the September issue of Agricultural Prices.

Procedure

Table 1 illustrates the method used in forecasting the season-average wheat price for the crop year 1999/2000. This method produces a forecast of the season-average price based on futures settlement prices. The procedure can be used daily, weekly, monthly or any other frequency to forecast the season-average price. The forecast frequency for this analysis is weekly. The futures settlement price as observed on each Thursday is used for each of the nearby contracts. [1]

Eight steps are involved in the forecast process:

1. The latest available futures settlement prices (line 1) are gathered for the contracts that are trading. Settlement prices for Thursday, June 17, 1999, are used for illustration (line 1). Futures quotes are used for July, September, December 1999 and March, May, and July 2000 contract settlement prices.

2. Monthly futures prices are the settlement prices of the nearby contracts. For example, the futures price for June 1999 (line 2) represents the June 17 settlement price of the July 1999 contract. The nearby (September) contract price will be used for July and August. During months which a futures contract matures, the next contract month is used because of greater stability. Futures contracts are affected by a decline in liquidity during the month of maturity. Also, a contract usually closes about the third week of the month, and using the current futures contract would lower the number of observations that could be used to calculate the average monthly closing price.

3. A 5-year moving average basis (monthly cash price minus the nearby futures price) is entered on (line 3) from the model's spreadsheet. This average is updated during the first week of July, a time when the May cash price becomes available.

4. A forecast of the monthly average farm price (line 4) is computed by adding the basis (line 3) to the monthly futures price (line 2).

5. The actual monthly average farm price is entered on line 5 as it becomes available. Since monthly cash prices are unavailable, this line remains blank until July when a mid-month June price can be used. This mid-month price is updated in August when the June cash price can be replaced with a entire month price and then a mid-month cash price is used for July, etc.

6. The actual and forecast farm prices are spliced together in line 6. For the present marketing year, 1999-2000, there are no actual monthly prices available and so all 12 monthly prices are forecasts (from line 4).

7. The monthly percentage of wheat marketings by producers is entered on line 7 from the model's spreadsheet. A 5-year moving average is used and is updated in early January after the release of the December Crop Production report for the years 1981 through 1997.

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[1] Thursday is picked because there are fewer holidays and no beginning and/or end of week surprises.

Beginning in 1998, this information is published in the September Agricultural Prices.

8. A weighted season-average farm price of wheat is then computed (line 8) by using the weights in line 7 and the monthly farm prices in line 6. A simple average annual price is also computed.

The futures forecasting model contains data for average monthly futures prices for the nearby contract, weekly futures prices of the nearby contracts, average monthly producer cash prices, and average monthly marketing weights. These data begin in 1981 and are updated to the present. The 5-year average for bases and monthly marketing weights begin with 1981-85 data and are updated to the present. A weekly futures forecast requires an update of weekly futures prices, available cash prices, and marketing weights on a periodic basis.

Price Forecasts for Crop Years 1999/2000 and 1998/99

Season-average price forecasts are based on expectations reflected in the futures market and, if available, actual farm prices. As of June 17,1999 the futures price forecast for crop year 1999/2000 for all U.S. wheat was $2.85 per bushel. On May 6, 1999 this forecast was $2.86 per bushel and during the 7-week forecast period ranged from $2.82 to 2.98 per bushel (figure 1). In comparison, the USDA's crop year farm price projection as released in its May and June WASDE reports for all wheat was $2.85 per bushel, a 7.5 percent increase above last year's estimated all wheat price of $2.65 per bushel. [2]

The June 1999 USDA outlook for U.S. wheat in 1999/2000 is for a smaller crop, increased exports, lower ending stocks, and slightly higher prices. However, projected wheat supplies are expected to be down only slightly because of higher beginning stocks. Ending stocks are expected to be the second largest in the 1990's, although they are expected to decline, compared to a year earlier.

Weekly futures price forecasts for the 1998/99 crop year are shown in figure 2. These forecasts are compared to the WASDE price projection in order to gain an idea of their reliability. Although WASDE price projections are made monthly, they are shown in a weekly frequency for ease of comparison to the futures price forecasts. Both methods' price projections were fairly similar and moved in the same direction between May 1998 and August 1998. Futures price forecasts rose relative to the WASDE projection in September through November because, in part, of a program announcement to donate U.S. wheat to needy countries and Southern Hemisphere production uncertainties. Starting in November 1998, the futures forecast drifted downward toward the WASDE projection because, in part, of a weaker global demand and more aggressive pricing by Australia and the EU. [3] Both projections converged in February and the estimated price for crop year 1998/99 is $2.65 per bushel.

Forecast Accuracy for Crop Years 1986/87 through 1998/99

Forecast accuracy is examined for crop years 1986/87 through 1998/99. Data for 1981 through 1985 were used to compute the 5-year average for bases and marketing weights. A mean absolute percentage difference is computed for each of the 13 forecast months within each crop year. This difference is computed between the monthly forecast and the actual season-average farm price. Next, a crop year forecast difference is computed, an average of a crop year's 13 monthly forecast differences.

Lastly, the futures forecasts are compared with the WASDE projections, an alternative published projection of the season-average price. Because the WASDE projections are released monthly, the weekly futures forecasts are averaged for each month in order to make a monthly comparison. [4] The midpoint of the WASDE projection range is used as the WASDE projection. It should be remembered that the futures forecast extracts information from futures prices and becomes a composite price forecast as monthly cash prices become available. The WASDE projection is a composite projection of econometric models, futures prices, analysts' judgement, and available monthly cash prices.

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[2] The mid-point of the WASDE projection range is used for comparison

[3] One reviewer pointed out that this decline in price forecasts could be due to monthly basis estimates that were too large. While this could be part of the reason, futher examination revealed that futures prices declined during this period and so cash price forecasts should decline. Additional analyses were completed assuming a perfect knowledge basis estimate and the cash price forecast also declined in this scenario.

[4] Another reviewer suggested that the monthly average price forecast should include the 4-weekly forecasts prior to the WASDE release date. This approach could be attempted in future research. The goal of this paper was to use available futures market information and compare its forecasts with the WASDE mid-point price

Monthly

Monthly forecast differences for both forecast methods of the season-average producer price for all wheat are shown in figure 3, crop years 1986 through 1998. As expected, for either forecast method, the average monthly difference is larger in the beginning of the forecast period and declines over time as more information becomes available. It is interesting to note that the futures forecasts generally have a larger average difference for the first several months, May and July, compared to WASDE projections. Does the futures market provide a higher risk premium during this period or does USDA have better market information? For the next five months, August through December, futures forecasts have a slightly lower error than WASDE projections. Does this suggest that traders' information is better than USDA's information? For the remainder of the year, January through May, both methods provide about the same forecast.

Annual

Crop year forecast differences for both forecast methods of the season-average producer price for all wheat are shown in figure 4, crop years 1986 through 1998. The average forecast difference for either method and for all crop years is 4.6 percent.

This finding tends to support Tomek's statement that over time both methods should provide similar forecasts. The futures forecast was quicker to pick up the price rise in 1995/96 than WASDE projections, but slower than WASDE projections to recognize its decline in 1996/97, thus explaining the differences between each method's forecasts for those years (figure 4).

Effects of Different Bases or Monthly Marketing Weights on Price Forecasts

Both the basis and monthly marketing weights are two variables that could significantly affect the futures forecast.

Basis

As mentioned earlier, a 5-year moving average basis is used in this analysis. However, what are the price forecast effects of an alternative basis? The 1996/97 crop year is analyzed because the largest difference between the two forecast methods occurred during this year, 3.1 percentage points. A 2-year average basis was computed based on crop years 1989 and 1991, years where the monthly basis was larger than normal. This 2-year average basis was expected to be similar to the bases in the 1996 crop year.

While the alternative 2-year basis improved the futures price forecast by .19 percentage points, this improvement was not very large (figure 5). Improvements in the futures forecast occurred in July, August, and September but were mostly offset with declines in October, November, and December.

A perfect knowledge basis was tried for the 1996/97 crop year price forecast, but it did not improve forecast accuracy. The reason why the forecast was not improved will require additional research. Additional basis forecasting techniques warrant further examination to determine their effects on the price forecast for different years.

However, improved basis forecasts for crop year 1996/97 may not help much because over 70 percent of the average forecast differences originate in the May through July forecasts. Unless those monthly forecasts are improved, it would be difficult to substantially improve the total crop year forecast.

Marketing Weights

Actual marketing weights were used for the 1996/97 crop year, in contrast to the 5-year average weights, to determine the effects on the price forecast. Results of this analysis are found in figure 6.

Using actual monthly marketing weights improved the futures forecast by .2 percentage points for crop year 1996/97. Improvements in the forecast occurred in May through September and again in February through May, but were nearly offset by declines in October through January.

While actual monthly marketing weights made a minimal improvement in the futures forecast for crop year 1996/97, further analysis of alternative estimating techniques of this variable does not seem warranted for this crop year but could prove useful for other years.

Conclusions

This analysis demonstrates that the futures forecast method can provide a timely and reasonable forecast of producers' season-average prices. This procedure can provide a useful tool for commodity analysts who need similar forecasts. The futures forecast method can also provide a useful cross-check against other season-average price forecasts.

While improved estimates of bases and monthly marketing weights improved the futures price forecast for crop year 1996/97, the effect was slight. Further research should examine the forecast effects of alternative estimates for bases and marketing weights for the other crop years analyzed in this study. Improved estimates of bases or marketing weights should improve forecasts in crop years where information is more certain. It appears that futures prices may have higher risk premiums early in the crop year forecast period when there is great uncertainty in market information.

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Table 1--Futures forecast of U.S. wheat producers' season average price, crop year 1999-2000

Item	June	July	August	September	October	November	December	January	February	March	April	May	July
							Dollars/Bushel						
(1) Current futures price 1/ by contract (settlement)		2.80		2.91			3.05			3.17		3.24	3.29
(2) Monthly futures price based on nearby contract	2.80	2.91	2.91	3.05	3.05	3.05	3.17	3.17	3.17	3.24	3.24	3.29	
(3) Plus the historical basis (cash less futures)	-0.25	-0.31	-0.21	-0.15	-0.21	-0.18	-0.13	-0.16	-0.20	+0.04	-0.20	-0.05	
(4) Forecast of monthly average farm price	2.55	2.60	2.70	2.90	2.84	2.87	3.04	3.01	2.97	3.28	3.04	3.24	
(5) Actual monthly farm price													
(6) Spliced actual/forecasted monthly farm price	2.55	2.60	2.70	2.90	2.84	2.87	3.04	3.01	2.97	3.28	3.04	3.24	
Annual price projections:													
(7) (Marketing weights in percent)	9.64	17.52	11.00	9.00	7.06	6.12	8.72	9.46	6.10	5.92	5.00	4.46	
(8) Weighted average 2.85													
Simple average	2.92												

1/ Contract months include: July, September, December, March, and May. Futures price quotation from the Kansas City Board of Trade, June 17, 1999 settlement.

Figure 1. Producers' Season Average Price Forecasts

For All Wheat, Crop Year 1999-2000

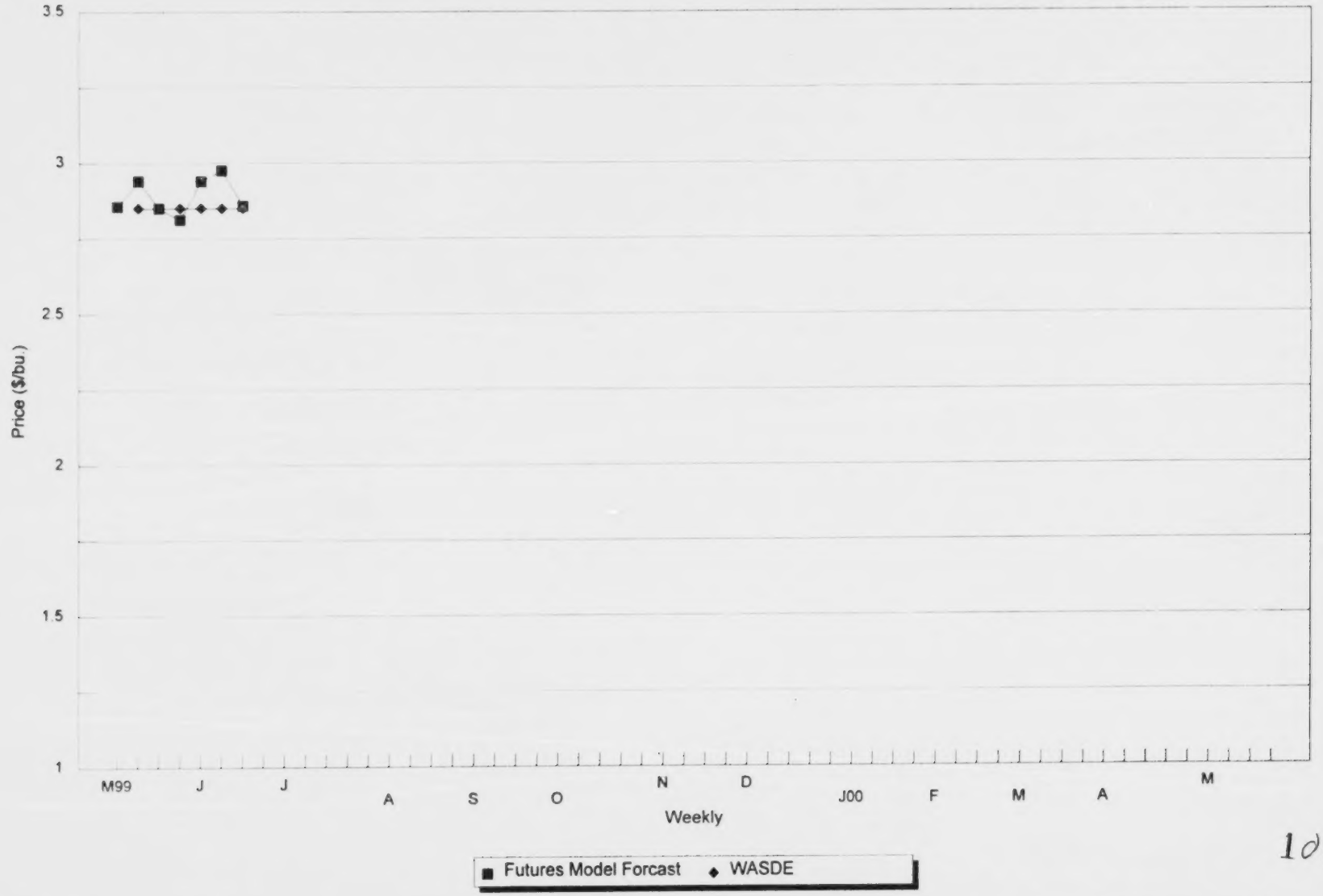


Figure 2. Producers' Season Average Price Forecasts

For All Wheat, Crop Year 1998-99

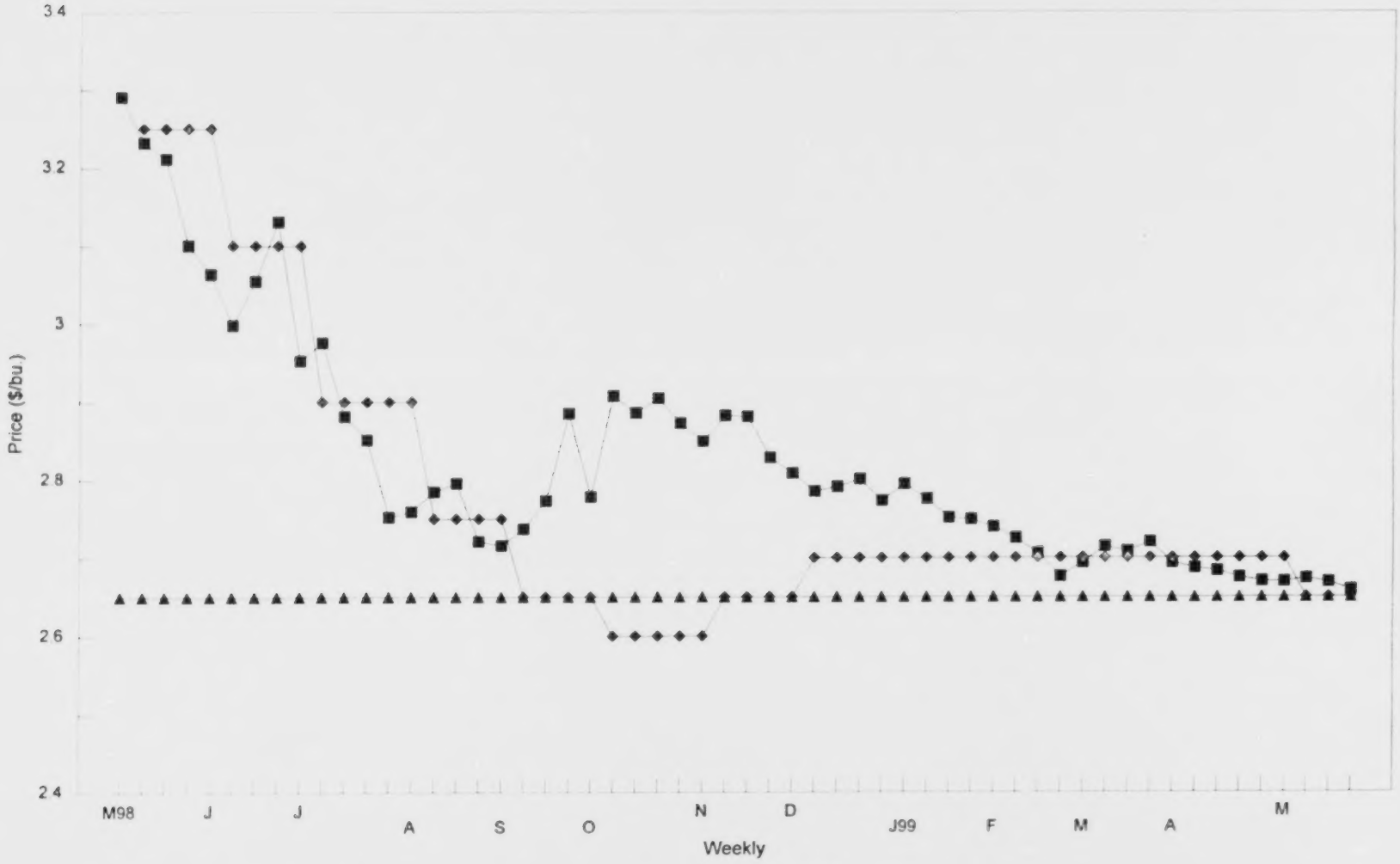
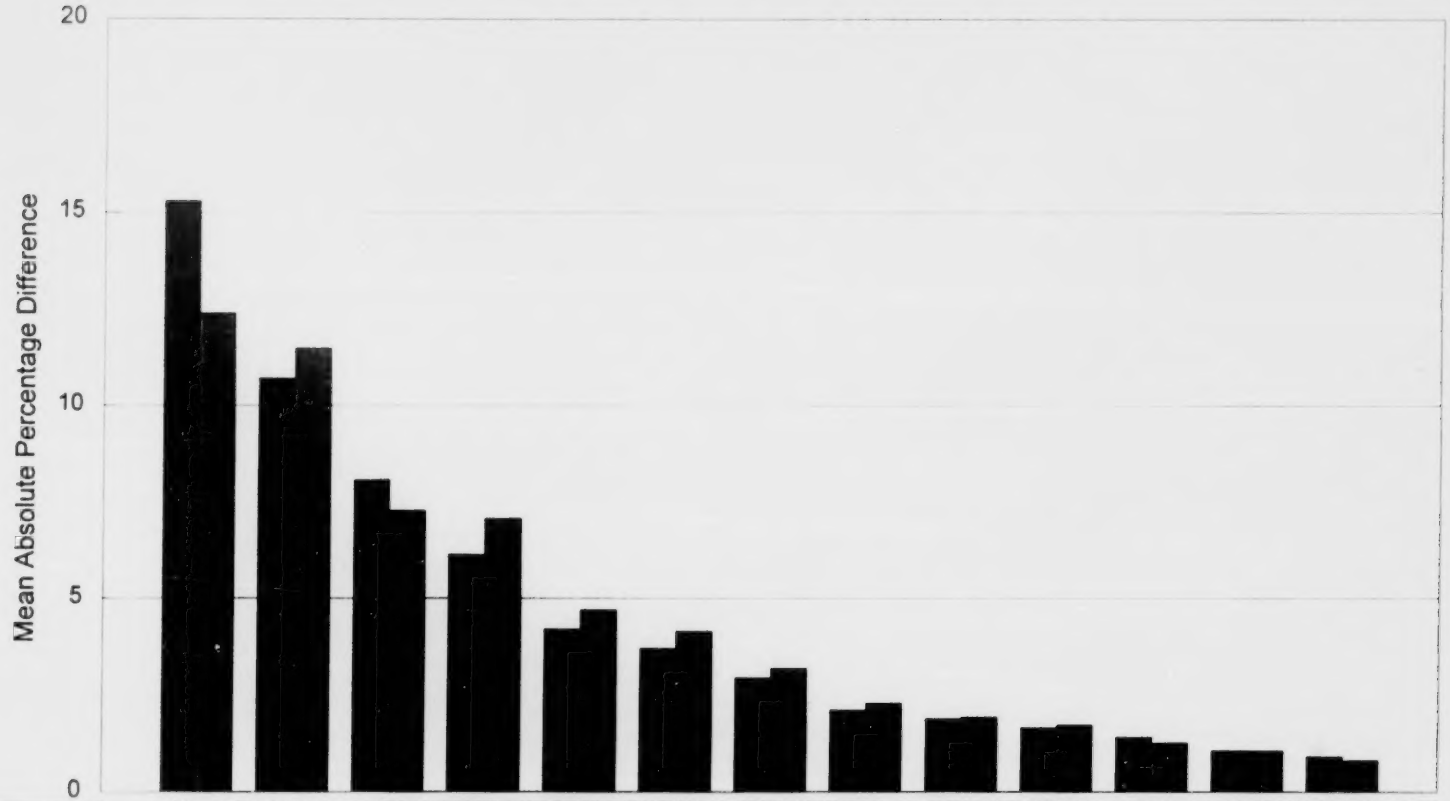


Figure 3. Accuracy of Monthly Season-Average Price Forecasts

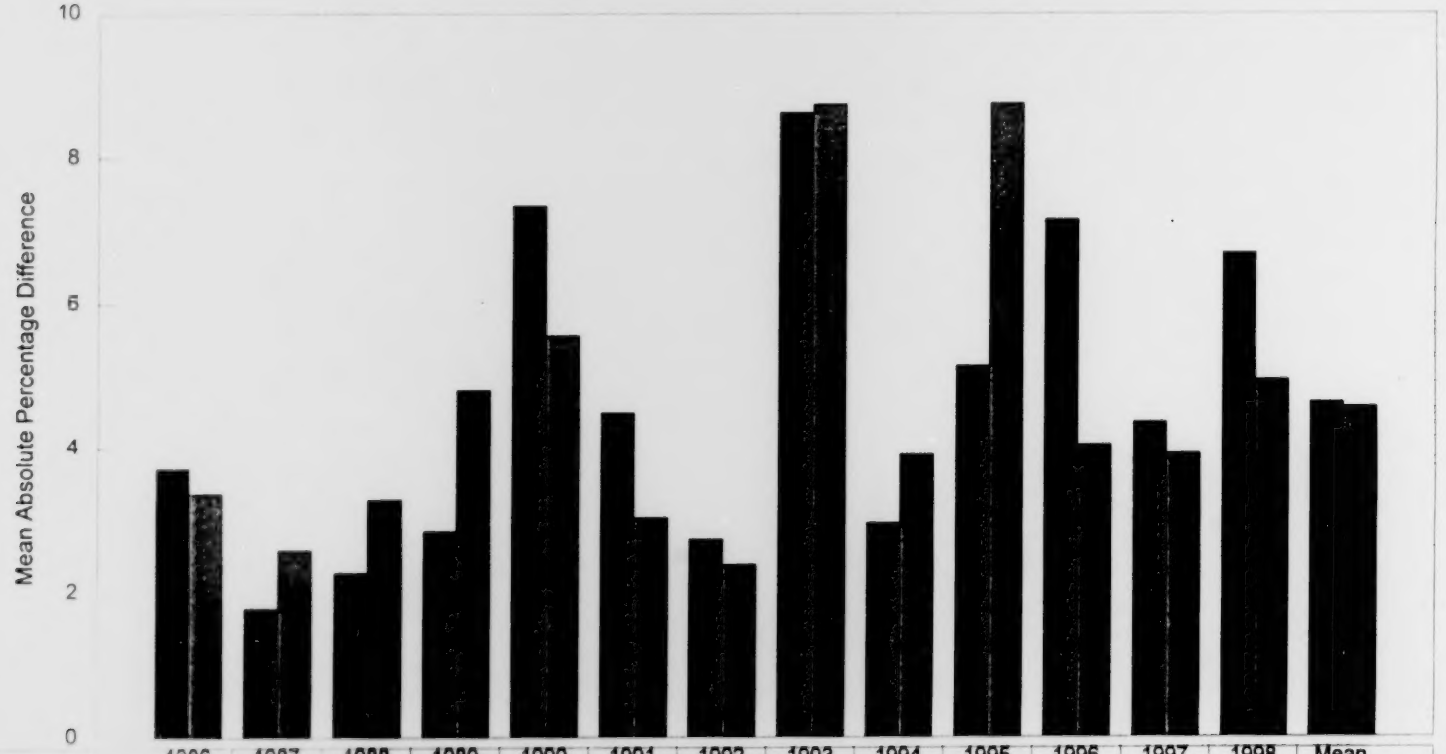
All Wheat, Crop Years 1986-1998



Month	May	June	July	Aug	Sept	Oct	Nov	Dec	Jan	Feb	Mar	April	May
Futures Model	15.30	10.71	8.06	6.12	4.19	3.69	2.94	2.11	1.89	1.66	1.41	1.06	0.90
WASDE	12.41	11.49	7.26	7.06	4.68	4.13	3.18	2.28	1.93	1.72	1.26	1.05	0.81

Figure 4. Accuracy of Season-Average Price Forecast

All Wheat, Crop Year 1986-1998



Marketing Year	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	Mean
Futures	3.72	1.78	2.27	2.84	7.34	4.48	2.73	8.63	2.95	5.13	7.1	4.35	6.69	4.62
WASDE	3.37	2.59	3.28	4.80	5.56	3.03	2.37	8.74	3.90	8.75	4.03	3.91	4.94	4.56

Figure 5. Futures Monthly Forecast of Season-Average Wheat Price

Effects of an Alternative Basis, Crop Year 1996/97

Month	May	June	July	Aug	Sept	Oct	Nov	Dec	Jan	Feb	Mar	April	May	Mean
5-Year Average	36.9	22.5	13.0	7.8	1.8	0.4	0.9	0.3	0.6	1.4	2.3	2.6	2.4	7.1
2-Year Avg. Expectation	36.9	22.5	11.2	5.9	0.1	1.9	2.2	1.4	0.2	1.0	2.1	2.7	2.4	7.0

Figure 6. Futures Monthly Forecast of Season-Average Wheat Price

Effects of Alternative Monthly Marketing Weights, Crop Year 1996/97

Month	May	June	July	Aug	Sept	Oct	Nov	Dec	Jan	Feb	Mar	April	May	Mean
5-Year Average	36.9	22.5	13.0	7.8	1.8	0.4	0.9	0.3	0.6	1.4	2.3	2.6	2.4	7.1
Perfect Forecast	36.1	22.0	12.4	6.6	0.0	2.7	3.5	2.8	1.9	0.8	0.4	0.7	0.4	6.9

MARKET ANALYSIS AND U.S. COTTON PRICES

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Cotton is one of the world's most important textile fibers, accounting for about 45 percent of fiber production. In 1997/98, U.S. farmers accounted for over 20 percent of the world's production of cotton, while U.S. mills used 13 percent of the world total or 20 pounds of cotton for each person in this country. And, because cotton is a major raw material for the textile and apparel industries, cotton production, marketing, and manufacturing affect the lives of many people from producers to consumers.

Since cotton is such a vast and dynamic industry, accounting for more than $25 billion in products and services annually in the United States, events that affect the cotton sector and cotton prices are monitored closely. Many interrelated factors help determine the price of U.S. cotton, such as the fundamental elements of supply and demand. In addition, the effects of agricultural policy also play a key role in influencing price relationships. These factors have various implications for the cotton industry, as well as many other industries, that extend well beyond the farm gate.

Background

Recent agricultural legislation has altered the nature of U.S. Government commodity programs, advancing the efforts toward increased market orientation. In particular, the 1996 Farm Act decoupled the income support programs that were in place for many years, and shifted the price volatility risk from the government to producers (see Young and Westcott). As a result, market information has become increasingly essential as producers and other market participants seek to make informed pricing decisions under a more market-oriented agricultural environment.

The U.S. Department of Agriculture (USDA) analyzes and publishes monthly supply and demand data and information pertaining to the major agricultural commodities. In addition, USDA publishes forecasts of season-average farm prices for these commodities. Cotton is the exception, however, as USDA is prohibited by law from publishing cotton price forecasts (see Townsend, 1989). Nonetheless, USDA calculates unpublished cotton price estimates for internal Departmental use each month along with the other reported U.S. and foreign cotton supply and demand estimates. Additionally, USDA analysts examine reasons explaining historical movements in commodity prices, including cotton prices.

This paper analyzes some of the factors that have historically influenced U.S. farm level cotton prices. An annual upland cotton price model is developed and designed to be used by USDA with other price estimation techniques in the analysis of market forces affecting the supply and demand for cotton. For an annually produced crop like cotton, ending stocks for a particular year summarize these supply and demand forces and can be a useful indicator of price movements. Annual cotton prices tend to be negatively correlated with ending stocks; high stocks of cotton tend to depress prices while low stocks tend to support prices, all other things being equal.

Agricultural policies and programs, such as the nonrecourse loan program, have also influenced prices, although the results of these programs have differed under the various farm policy environments. The basic loan program allows producers to obtain loans for a commodity, in exchange for placing that commodity as collateral in approved government storage. At the producer's option, the loan, including any accrued interest and/or storage charges, can be repaid at any time during the loan period, or the commodity can be forfeited to the government at the end of the loan period if market prices are not high enough to make economic sense for the producer to repay the loan. For upland cotton, significant forfeitures occurred in the early 1980's.

However, with the passage of the 1985 farm legislation, a new program, the marketing loan, provided a repayment option below the loan rate for upland cotton when the U.S. price was not competitive on the world market. The 1985 Act allowed upland cotton producers to repay loans at the lower of the loan rate or the adjusted world price (AWP). The marketing loan remains in effect under the 1996 Act and has eliminated the large forfeitures seen in the past.

Like many commodities, there is no single price for cotton, as numerous daily, monthly, and annual price series reflect different markets, qualities, and/or delivery times. Nevertheless, each series is linked by the fundamental elements of supply and demand. Previous research addressing factors affecting commodity prices has included the basic elements of supply and demand in the form of the stocks-to-use ratio. This ratio is defined as the stock level of a given commodity at the end of a particular period divided by the total use of that commodity for that same period. Like ending stocks, the stocks-to-use ratio provides a good summary of the year's

supply and demand situation and, more importantly, the stocks-to-use ratio is comparable over time. Similar to the research by Collins, Townsend, and Westcott, the stocks-to-use approach was employed as the basis for this price determination analysis.

This paper presents efforts by the Economic Research Service to reevaluate factors affecting farm price movements for major commodities under the more market-oriented agricultural environment. While the annual estimate of the average U.S. upland cotton farm price, in and of itself, may be less useful to those who must follow monthly or daily prices, the factors that influence the annual price provide a framework that allows a better understanding of intra-year price movements and perhaps a more informed decision about cotton price movements in general.

Model Framework

The basic framework used here relating prices to ending stocks follows a general equilibrium model. Following an example by Westcott, with the model in its simplest form, supply, use, and stocks are each a function of price, including a market-clearing, equilibrium condition where supply equals use plus stocks:

$$\text{Supply} = f_1(\text{Price})$$

$$\text{Use} = f_2(\text{Price})$$

$$\text{Stocks} = f_3(\text{Price})$$

$$\text{Supply} - \text{Use} - \text{Stocks} = 0$$

With the system in equilibrium, prices can be determined from the inverse of the supply, use, or stocks function. Taking the inverse of the stocks function yields a price determination equation in which prices are negatively related to stocks:

$$\text{Price} = f_3^{-1}(\text{Stocks})$$

As previously stated, ending stocks of an annually produced commodity like cotton reflect the relationship between supply and use. If use expands relative to supply, stocks decline and prices tend to rise as a result. On the other hand, if use falls relative to supply, stocks rise and prices tend to decline, all other things being equal. Therefore, the stocks variable is transformed to reflect stocks relative to total use, an important indicator of the "scale of activity" in the cotton sector. For example, a particular level of stocks today represents a smaller portion of total use than the same stock level two decades ago. The transformation captures the sector's growth over time and is a measure of the commodity's relative market tightness. The result is a stocks-to-use variable commonly used in price models and is presented in the following equation:

$$\text{Price} = f_3^{-1}(S/U, z)$$

where S/U represents the ratio of stocks-to-use and z represents a set of exogenous variables that can shift the relationship between the stocks-to-use ratio and the price. This basic model is used here, with adjustments introduced that shift the price relationship.

Model Specification

The following functional form was used in estimating annual upland cotton farm prices:

$$\text{Ln (PRICE)} = a + b\,\text{Ln (S/U)} + c\,\text{CHFSTKS} + d\,\text{INDEX} + e\,\text{DSU} + f\,\text{Ln (1+LDP)} + g\,\text{Ln (1+CCC/U)}$$

Definitions of the variables used in the model are discussed below and are summarized in table 1. The dependent variable is the natural log of the marketing year average price received by upland cotton producers. This price, published by USDA, is a weighted annual price based on marketings throughout the year and is reported in cents per pound.

The price model's independent variables hypothesized to affect prices account for both U.S. and foreign market supply and demand conditions and U.S. agricultural policy programs, which have altered the supply and demand of cotton in the past. These variables also capture information that is readily available for timely modification of the model's estimate.

The basic model relates stocks-to-use ratios to prices. The S/U variable is the upland stocks-to-use ratio for a given year, and is reported as a percentage. This variable indicates the tightness of U.S. supplies relative to demand. Figure 1 shows a historical plot of U.S. farm prices for upland cotton and stocks-to-use ratios for the 1978 through 1996 marketing years. As the stocks-to-use ratio changes, the effect on prices is expected to be in the opposite direction. The variable is included in the model in logarithmic terms.

Other supply and demand conditions affecting price are introduced with the next three variables. The CHFSTKS variable is the percentage change for a given marketing year, from the previous year, of total foreign ending

stocks, excluding China's. This variable is representative of the foreign cotton supply and demand situation outside of China. As this variable changes, the effect on prices is expected to be in the opposite direction. For example, if the percentage change in foreign stocks (less China) declines from the previous season, this indicates that global cotton demand exceeded global supplies, so U.S. farm prices are expected to increase, all other things being equal.

Stocks in China are excluded from this variable partly because there has been much debate in the cotton industry over the size of China's stocks. Market analysis of the foreign cotton situation and outlook often omits China, as policy actions there pertaining to cotton do not always reflect responses to market supply and demand conditions, particularly related to stocks. However, because China is the largest producer and consumer of cotton, changes in China are important but are often reflected in the supply and demand balance sheets of other countries, including the United States. Therefore, omission of China stocks is not expected to reduce the overall effectiveness of the specified price model.

The INDEX variable weights the percentage of cotton crop acreage forward contracted by the end of September of a given year multiplied by the September average of the December futures contract of the same year. The index is inversely related to early season supply expectations. For example, if supply expectations are low, December futures tend to be higher and therefore more acreage tends to be forward contracted. And, because the farm price is based on marketings (including forward contract deliveries), the larger the percentage of acreage forward contracted, the greater role the index plays in determining the marketing year average price. Thus, the index is positively related to price.

The DSU variable represents the effects of starting a new marketing year with very tight beginning stocks. DSU is a dummy variable equal to one in years when the stocks-to-use ratio of the previous year is less than or equal to 22.5 percent and zero in all other years. During the sample period, the stocks-to-use ratio was less than or equal to 22.5 percent in 1979-1980, 1983, 1989-1991, and 1993-1996. Therefore, DSU is equal to one in the marketing year following each of these years. When the stocks-to-use ratio of a given year is less than or equal to 22.5 percent, the subsequent marketing year's prices may be high and total use may be limited, particularly in the early months before the new crop is harvested and becomes available. This variable is an intercept shifter and is expected to have a positive sign.

The next two variables are program variables related to current or past agricultural policy. As established in the 1985 Act, a marketing loan provision provides a loan repayment plan if the basic loan rate is not competitive on the world market. When the adjusted world price (AWP) for upland cotton falls below the established loan rate, the producer can repay the loan at the AWP, thus establishing a lower effective loan repayment rate. And the difference between the established loan rate and this repayment rate is represented by the LDP variable. The LDP variable is the loan deficiency payment rate for upland cotton expressed in cents per pound. This program was first implemented for the 1986 marketing year to keep upland cotton loan stocks from being forfeited to the Government when prices are low. Since implementation, loan deficiency payments have been issued in only 4 years (1986 and 1991-1993) during the sample period and ranged from 6.35 to 11 cents per pound. Natural logs of one plus LDP are used in the model, keeping the transformed variable from falling below zero.

Loan deficiency payments are not included in the reported average price received by producers, therefore, the addition of this payment to the reported price would reflect a "more accurate" average effective price received by the producer. And since loan deficiency payments are made when market prices are low, a negative correlation exists between the transformed LDP variable and the price received by producers. This variable is an intercept shifter for the years when loan deficiency payments are made.

The final variable, CCC/U, represents agricultural policy prior to the 1986 marketing year. The CCC/U variable, which is the Commodity Credit Corporation (CCC) stocks divided by total use for a given year, is expressed as a percent. Natural logs of one plus CCC/U are used in the model, keeping the transformed variable from falling below zero. This program variable becomes relevant when CCC inventories are large, as during the 1982 through 1985 crop years when market prices for upland cotton were supported by the loan program and was influential in forfeitures to the CCC. Between 1982 and 1985, CCC inventories of upland cotton, ranging from 124,000 to 775,000 bales, were substantially larger than at any other time during the data period analyzed. The transformed variable is positively related to price and is an intercept shifter for years when CCC inventories of upland cotton are held.

Results

The upland farm price model was estimated using ordinary least squares regression, using annual data for

marketing years 1978 through 1996. The estimated regression equation is:

$$\begin{aligned}\text{Ln (PRICE)} = {} & 4.3338 - 0.1002\ \text{Ln (S/U)} - 0.0029\ \text{CHFSTKS} \\ & \quad (-4.93) \qquad\quad (-4.05) \\ & + 0.0057\ \text{INDEX} + 0.0631\ \text{DSU} - 0.0408\ \text{Ln (1+LDP)} \\ & \quad (5.30) \qquad\quad (3.31) \qquad\quad (-4.25) \\ & + 0.0742\ \text{Ln (1+CCC/U)} \\ & \quad (4.13)\end{aligned}$$

Adjusted R-squared = 0.9273
F-statistic = 39.25
Standard error of the estimate = 0.03048
Durbin-Watson statistic = 1.781
Degrees of freedom = 12

Nearly 93 percent of the variation in (the log of) annual upland cotton prices is explained by the equation. The numbers in parentheses below each coefficient are the t-statistics. Each coefficient has the expected sign and each is significant at the 1-percent level.

Model Performance

Figure 2 shows historical upland cotton farm prices and the associated predicted values derived from the estimated equation. As illustrated, the price model tracks actual cotton prices well, capturing each turning point during the 1978-96 period. Most differences between the actual upland farm price and the model estimate are less than 1.5 cents per pound.

In addition, mean absolute errors and mean absolute percentage errors were calculated for the full estimation period, and for selected subsamples of recent marketing years. Throughout the entire estimation period, the mean absolute error was 1.3 cents per pound, while the mean absolute percentage error was 2.1 percent. During one subsample period covering the 1991-1996 marketing years, the errors are slightly higher due mainly to the model's underestimation in 1996. For the 1991-1996 period, the mean absolute error was 1.4 cents per pound, while the mean absolute percentage error was 2.3 percent. However, if 1996 is excluded from the subsample, the mean absolute error declines to 1.2 cents per pound and the mean absolute percentage error decreases to 2.0 percent. These statistical measures indicate good performance of the upland cotton pricing model.

Model Features

Upland stocks-to-use ratios have been below 30 percent since 1988, although they ranged from 13 to 113 percent during the estimation period. While stocks-to-use ratios for upland cotton are expected to remain at or below the 30-percent level under the current policy environment, the various features of the regression equation results are illustrated using stocks-to-use ratios ranging from 5 to 60 percent.

A base model relationship was first determined by varying stocks-to-use while holding DSU equal to one, the CHFSTKS and INDEX variables equal to their sample means, and zeroes for the other variables (see table 2). The base model results (solid-line curve) and the different features of the regression model are illustrated in figures 3 through 7. For each graph, upland cotton prices are plotted against ending stocks-to-use ratios, adjusting the variables from logarithms to levels. The base model curve is identical in each figure. Therefore, each graph illustrates the effect of shifting one explanatory variable at a time from the base model values, highlighting that variable's influence on prices.

The base model equation and the effects of the previous year's stocks-to-use ratio on cotton prices are shown in figure 3. The higher (base model) price curve incorporates the effect of upland stocks-to-use ratios in the previous year of less than or equal to 22.5 percent (DSU=1). The lower dotted-line price curve represents the price effect of upland stocks-to-use ratios in the previous year of greater than 22.5 percent (DSU=0), holding all other independent variables at their base model values. Price impacts shown in figure 3 range from -3.5 to -4.6 cents per pound when the previous year's stocks-to-use ratio is greater than 22.5 percent when compared with the base model.

Figure 4 illustrates the effects on cotton prices for different percentage changes in foreign stocks less stocks in China. The base model is again represented by the solid-line curve, while the two dotted-line curves represent one standard deviation above and below the sample mean of the variable, CHFSTKS. This deviation corresponds to a 13.2-percentage-point increase in foreign stocks (less China) and an 11.2-percentage-point decrease. Compared with the base model, price impacts illustrated here are -2.0 to -2.6 cents per pound with the increase in competitor stocks and 2.2 to 2.8 cents per pound with the decrease in competitor stocks.

Figure 5 indicates the sensitivity of the upland cotton price function for different INDEX values related to the amount of the crop that was forward contracted and the level of the December futures contract. The base model along with the two dotted-line curves, representing one

standard deviation above and below the sample mean, are pictured. One standard deviation above the mean corresponds to an index of 26.1, while one standard deviation below corresponds to an index of 5.0. Price impacts shown here range from 3.6 to 4.6 cents per pound with the higher index and -3.3 to -4.3 cents per pound with the lower index when compared with the base model.

As indicated from the results in figures 4 and 5, one standard deviation around the INDEX variable causes a greater impact on prices than one standard deviation around the CHFSTKS variable. However, the INDEX variable would be finalized early in the marketing year (early October), while the competitor stocks variable typically changes each month throughout the season as better information and data become available. Therefore, the effect on prices of the CHFSTKS variable may change several times throughout the season, unlike the INDEX variable.

The effect of loan deficiency payments on upland cotton prices is shown in figure 6. The upper curve represents the base model when no loan deficiency payments are made. The lower dotted-line curve, on the other hand, illustrates the price effect of loan deficiency payments averaging about 9 cents per pound, corresponding to the mean logarithmic value of these payments for the 1986 and 1991-1993 marketing years. As discussed earlier, these payments are not included in the reported farm price for upland cotton. Therefore, the payment value should be added to the reported price to get a "more representative" indicator of the effective price received by producers in years when loan deficiency payments are made. Price impacts shown in figure 6 range from -5.2 to -6.7 cents per pound, compared with the base model, corresponding to average loan deficiency payments of about 9 cents.

Figure 7 illustrates the effect of CCC stocks on cotton prices. The solid-line curve represents the base model when there are no inventories of CCC stocks. The upper curve indicates the price supporting effect of having stocks unavailable to the marketplace and held as CCC inventory. The dotted-line curve represents a CCC stocks use ratio of about 3 percent, corresponding to the mean logarithmic value of the 1982-1985 marketing years, the period when CCC inventories of cotton were much higher than at any other time during the estimation period. Price impacts illustrated on the graph range from 6.3 to 8.0 cents per pound when average CCC stocks/use ratios of about 3 percent are present when compared with no CCC stocks.

Out of Sample Estimate

One of the largest errors in the model occurred in the last year of the estimation period, 1996. So, there was a concern about the model's performance in future years. Did the 1996 farm legislation provide additional factors, not accounted for in this model, that were more influential in determining farm prices than in the past? To address this concern, the price model presented here was used to estimate a farm price for upland cotton for the first out-of-sample period, the 1997 marketing year that ended in July 1998. Model variables use the latest available data (June 1999) for the 1997 marketing year and are not expected to change significantly.

The model estimated the 1997 marketing year average price for upland cotton to be 62.5 cents per pound, while the actual farm price, reported by USDA, was 65.2 cents per pound. As a result, the first out-of-sample estimate derived from the regression equation underestimated the actual price by 2.7 cents per pound, or slightly greater than one standard error of the model estimate (transformed from logarithms to price levels). With limited data, however, it was difficult to determine whether the 1996 farm legislation had introduced "new" factors that influence farm prices.

Consequently, data for the current marketing year, 1998, was collected and analyzed. In addition to internal Departmental forecasting, the 1998 price estimates have been used as a gauge to help determine if the model's underestimation which occurred in 1996 and in the out-of-sample estimate for 1997 could be associated with the recent change in farm legislation. Although nearing the close of the 1998 season, which ends July 31, 1999, a lag in the price data only provides a 9-month average farm price of 61.3 cents per pound. However, because this price is a weighted price, with most of the weight historically associated with earlier months, the annual average should not vary significantly from this reported 9-month average.

Incorporating June 1999 data, the model presented here was used to make a two-step ahead extrapolation estimate for the 1998 season. Because USDA is prohibited by law from publishing cotton price forecasts, however, results can not be reported here. But, barring any substantial changes to the U.S. or foreign cotton supply and demand estimates, it is likely that the 1998 price estimate (based on the regression equation) will prove to be much closer to the actual price than in the previous two seasons and would fall well within one standard error of the model estimate when transformed from logs to price levels.

Conclusions

The upland cotton price determination model presented here uses a stocks-to-use ratio framework. In addition, the model addresses issues regarding the historical influence of government commodity loan and storage programs on cotton prices. These programs were shown to have affected upland cotton price determination during the early 1980's, prior to the passage of the 1985 farm legislation. With the implementation of the 1985 Act, however, storage programs have not influenced upland cotton prices significantly, but the cotton loan program remains an important component. As U.S. prices are more closely tied to world market conditions, foreign market supply and demand expectations, as well as U.S. conditions, have played a larger role recently in affecting the price received by U.S. upland cotton producers. The stocks-to-use ratio and other variables identified in the model have shown the importance of market supply and demand factors on upland cotton price determination.

The statistical model's evaluation measures and the graph illustrating the actual prices and model estimates indicate the effectiveness of the regression model in the determination of upland cotton prices. This is particularly relevant given the wide range in upland cotton prices over the sample period (1978-1996), as well as the changes in agricultural policy that have had varying impacts on prices. While there was some concern with the model's underestimation in 1996 and 1997, preliminary results for 1998 are promising. Although annual monitoring may be necessary, the price determination model as presented seems to adequately capture those factors influencing upland farm prices and additional variables do not seem appropriate at this time.

With carryover stocks of upland cotton as a percent of total use typically smaller in the 1990's than in any previous period, price determination is in the steeper portion of the price function and implies more price responsiveness to shocks. However, with the continued full planting flexibility currently in place, market signals and producers' responses to these signals may help mitigate the large annual variability in upland cotton prices seen in the past.

Finally, the relatively simple structure and the limited data needs of the regression model presented here allow for sensitivity analysis under various market supply and demand conditions that may develop during a given year or from one year to the next. While USDA does not publish cotton price forecasts, this model, along with other models, is used to analyze historical cotton price movements and is used in USDA's short-term market analysis as well as long-term baseline projections.

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Table 1--Variable definitions used in the upland cotton price model specification

Variable	Definition
PRICE	Marketing year average price received by upland cotton producers and expressed in cents per pound.
S/U	Upland cotton stocks-to-use ratio and expressed as a percent.
DSU	Dummy variable equal to one when the previous year's stocks-to-use ratio is less than or equal to 22.5 percent, and zero in all other years.
CHFSTKS	Change from the previous year in foreign stocks minus China's stocks and expressed as a percent.
INDEX	Percentage of upland cotton forward contracted by the end of September multiplied by the September average of the December futures contract.
LDP	Loan deficiency payment rate for upland cotton and expressed in cents per pound.
CCC/U	Commodity Credit Corporation upland stocks divided by total upland use and expressed as a percent.

Table 2--Upland cotton price model assumptions used in model feature illustrations

Variable	Base model values	Shift values
S/U	5 - 60%	5 - 60%
DSU	1	0
CHFSTKS	1.03%	13.21% and -11.15%
INDEX	15.53	26.07 and 4.99
LDP	0	8.8 cents
CCC/U	0	2.9%

Note: Base model value for DSU corresponds to beginning stocks-to-use of less than or equal to 22.5 percent, representative of the current situation. Base model values for CHFSTKS and INDEX equal sample means, while shift values equal the mean plus and minus one standard deviation. Shift value for LDP corresponds to the 1986 and 1991-1993 mean logarithmic value of the transformed variable (1+LDP). Shift value for CCC/U corresponds to the 1982-1985 mean logarithmic value of the transformed variable (1+CCC/U).

Figure 1

Upland cotton prices and stocks-to-use ratios, 1978-1996 marketing years

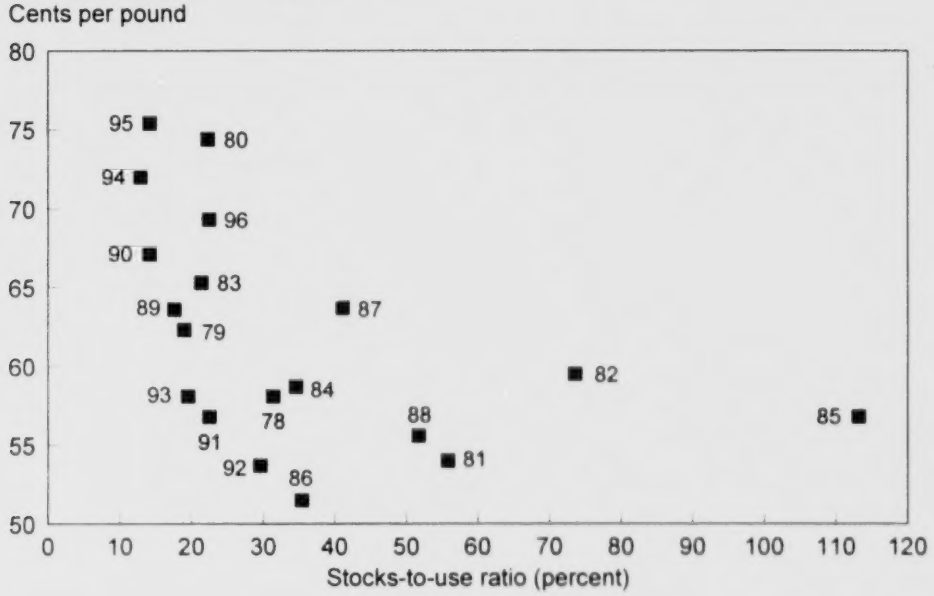


Figure 2

Upland cotton prices--Actual and model estimate

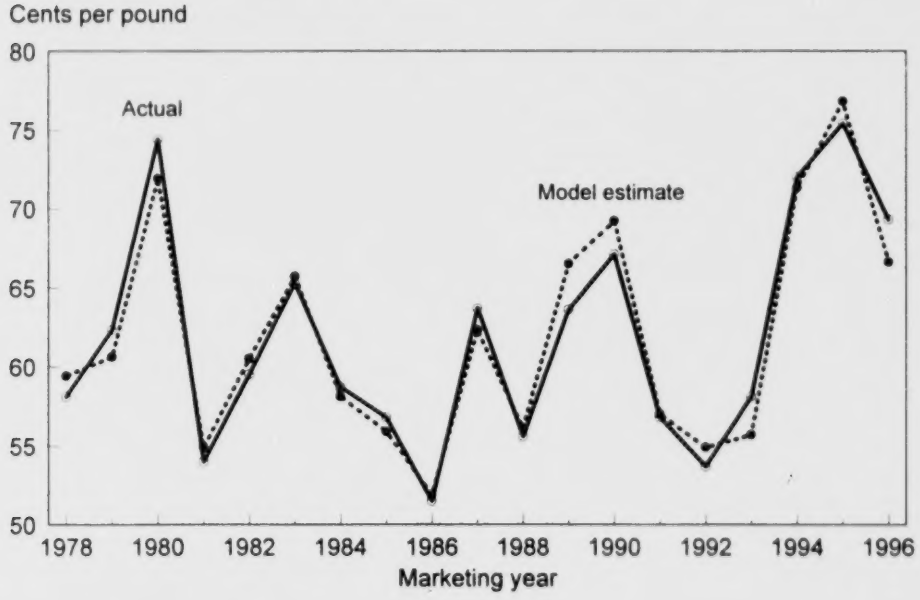
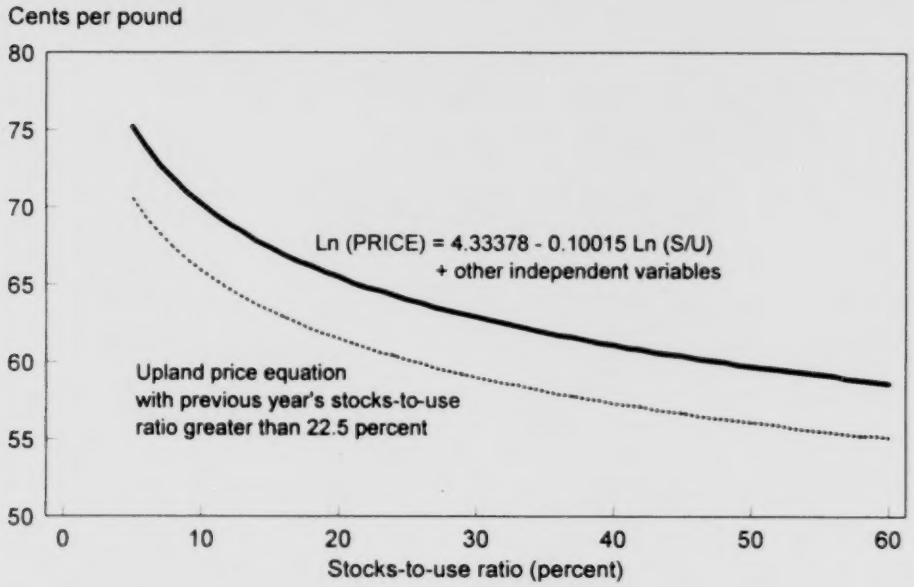


Figure 3

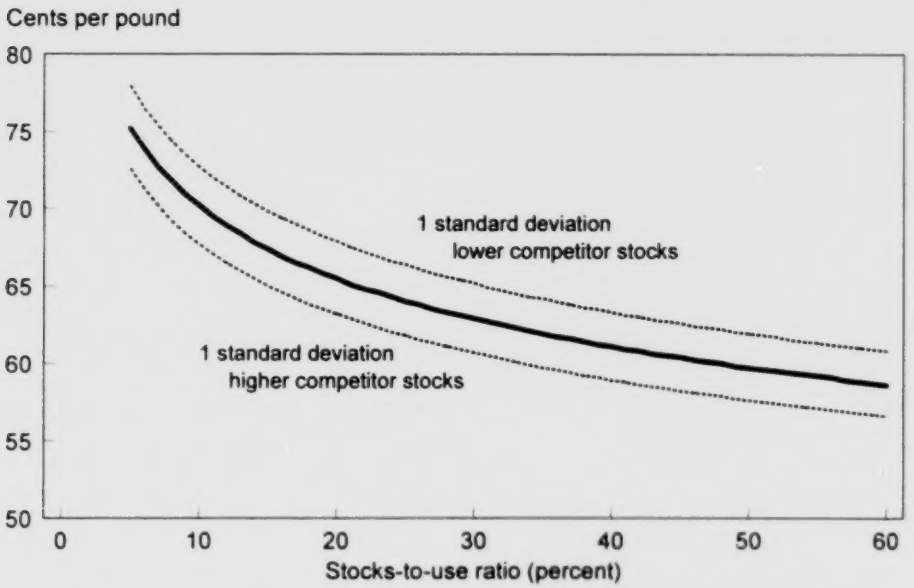
Upland price equation--Previous year's stocks-to-use effect



For each curve, other independent variables evaluated at their base model values (see table 2).

Figure 4

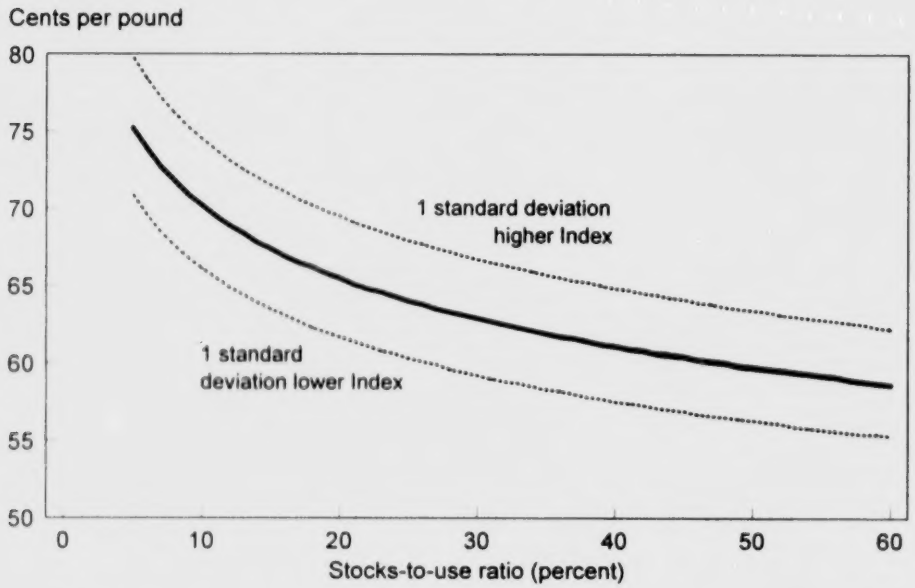
Upland price equation--Foreign stocks less China effect



For each curve, other independent variables evaluated at their base model values (see table 2).

Figure 5

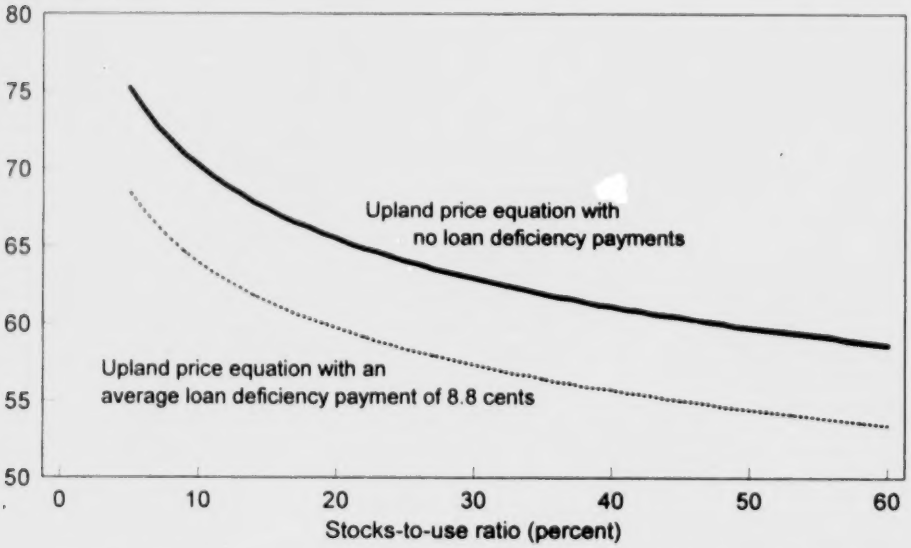
Upland price equation--Forward contract index effect



For each curve, other independent variables evaluated at their base model values (see table 2).

Figure 6

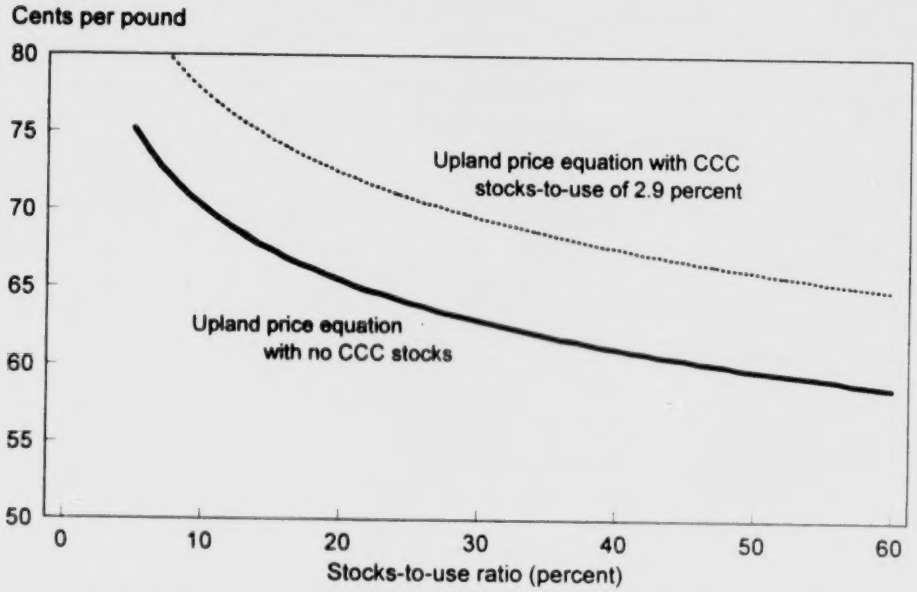
Upland price equation--Loan deficiency payment effect



For each curve, other independent variables evaluated at their base model values (see table 2).

Figure 7

Upland price equation--CCC stocks-to-use effect



For each curve, other independent variables evaluated at their base model values (see table 2).

PRODUCTION AND PRICE IMPACTS OF U.S. CROP INSURANCE SUBSIDIES: SOME PRELIMINARY RESULTS

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Introduction

Federally-backed crop and revenue insurance programs help to ease the financial shocks that crop loss can impose on farmers, bankers, and rural communities. In recent years, the government's role in supporting agricultural risk management has been accentuated by a perceived reduction in the Federal agricultural "safety net" via the elimination of deficiency payments and a greater emphasis on letting market forces guide producers' planting and marketing decisions.

While Federally-subsidized crop insurance programs clearly have had a beneficial impact on recipient farms, communities, and regions, some analysts question whether crop insurance programs have had other, unintended consequences (Skees). The argument that Federal intervention is crucial to overcoming a failure by the private sector to provide affordable, universally-available multi-peril crop insurance has muted distortion-related concerns in the past. However, growing levels of subsidy outlays combined with certain design aspects of federal crop insurance intervention suggest that there exists the potential for significant unintended market effects.

This study is a preliminary attempt at assessing the extent of market distortion, as measured by acreage and production shifts, directly attributable to Federal crop insurance subsidies. Crop insurance subsidies, converted to commodity-specific price wedges, are incorporated into a national policy simulation model that accounts for intra- and inter-regional acreage shifts and cross-commodity price effects. The results suggest that such subsidies generate small shifts in aggregate plantings. Nationally, wheat and cotton acreage appears to gain the most from Federal crop insurance subsidies. Stronger effects emerge at the regional level as planted acreage shifts away from the Southeast and Far West and towards the Plains States. An additional important result is that price-feedback and cross-price effects tend to dampen the own-price effect, suggesting that acreage shifts are substantially smaller than results which ignore feedback and cross-commodity-price effects.

This paper is organized as follows. First, we examine the historical arguments for Federal intervention in crop insurance and its potential for distortion. Second, we discuss the methodology and data used to evaluate potential acreage distortions from Federal subsidies. Third, several limitations to the aggregate modeling approach adopted here are introduced. Finally, we present the preliminary empirical results–national and regional–and briefly discuss their implications from a broader market and trade framework.

Background on Federal Intervention in Crop Insurance Programs

The U.S. government has played a historically active role in targeting producers for protection against yield and revenue risks by developing, promoting, and subsidizing agricultural crop and revenue insurance. Such intervention has been justified on the grounds of a risk market failure due to private sector reluctance to provide universal, multi-peril crop insurance (Goodwin and Smith, 1995; Miranda and Glauber).

USDA's Federal Crop Insurance Corporation (FCIC) subsidies are designed to make crop and revenue insurance universally available, and to increase participation in such insurance markets. Premiums are subsidized up to a maximum of 42 percent. With respect to private companies, FCIC subsidies remove the delivery cost and underwriting risk from premiums paid by producers. With respect to producers, FCIC subsidies lower the direct cost of acquiring insurance such that expected benefits are greater than actual premium costs.

Federal outlays for crop and revenue insurance have grown significantly since the 1994 Federal Crop Insurance Reform Act (figure 1), averaging nearly $1.4 billion annually during the 1995-98 period. Program expenditures are projected to increase to approximately $1.7 billion in 1999. Current legislative proposals (under the rubric of insurance reform and developing a "farm safety net") would continue and in some cases increase the large subsidy transfers. Therefore, it is critical that

policymakers fully understand the market effects of such subsidies.

Several aspects of FCIC subsidy design suggest that there exists the potential for significant unintended consequences beyond their original purpose. ***First,*** when viewed as an increase in expected revenue, the premium subsidy provides an incentive to purchase insurance and to marginally expand area under crop production since a producer's expected benefit increases with every insured acre. ***Second,*** by calculating premium subsidies as a percent of total premium they favor production on riskier land where it might not otherwise occur. Since premiums are based on expected payouts, premiums (and therefore the subsidy) are higher on risker land. And to the extent that yield risk varies across both crops and fields, so too does any subsidy-induced distortion suggesting that distortions likely occur across both regions and commodities. ***Third,*** to the extent that federal administrative reimbursement subsidies and sharing of underwriting risk increase the likelihood of insurance delivery, and consequently production, in high risk areas (such as in various locations in the Great Plains), they likely lead to distortions across both regions and commodities.

In their review of crop insurance literature, Knight and Coble (1997) identified the importance from a policy perspective of quantifying how crop insurance programs affect acreage decisions, especially following the 1996 Farm Act policy changes. However, most previous related research has been limited to farm-level or regional partial equilibrium models of behavioral responses with respect to input use or crop insurance participation decisions, and have not looked at the effects of government crop insurance subsidies on aggregate production and prices across a variety of activities and risk environments. Farm- and regional-level partial equilibrium models are unable to capture the feedback effect that acreage response and its resultant production changes engender, while also frequently ignoring cross-commodity price effects. This study is a preliminary step attempting to address these research shortcomings.

Methodology Development

This study examines the influence of Federal crop insurance subsidies on planted acreage of eight major field crops–corn, wheat, soybeans, upland cotton, grain sorghum, barley, oats, and rice–for the entire U.S. and in each of seven major production regions. The seven production regions include the Northeast, Southeast, Delta, North Central, Central and Northern Plains, Southern Plains, and Far West (figure 2).

Although multiple-peril crop insurance is available in most major agricultural production regions and for most major agricultural field and specialty crops, the eight crops included in this study account for the majority of crop insurance activity. During the 1995 to 1998 period, these eight crops represented over 90 percent of insured acres and 72 percent of total insured liability, and received 76 percent of government premium subsidies and 74 percent of indemnity payments.

An evaluation of potential subsidy distortions begins by examining the extent of regional and crop-specific subsidy transfers in both absolute and relative terms. The subsidy includes both premium subsidies and estimates of crop and regional shares of the federal administrative/delivery cost reimbursements and net underwriting losses/gains.

County-level summary of business data on premiums, premium subsidies, indemnities, liabilities, and net acres insured are available for each crop, insurance program, and coverage level from USDA's Risk Management Agency (RMA).[1] Information on federal administrative/delivery reimbursements and net underwriting losses are also available from the RMA but only as national aggregates[2]. To make the model operational, each crop's share of aggregate subsidies (within each region) attributable to administrative reimbursement and underwriting risk sharing was estimated under the assumption that crops and regions with historically higher risk received a proportionally greater share of subsidy outlay. Approximations for each crop's share of administrative/delivery reimbursements and net underwriting losses were estimated at the state level by taking the 1994-98 average loss ratio minus one, times the total premium on "buy up" for each crop.[3]

The total crop and revenue insurance subsidy for a crop within a state is then defined as premium subsidies plus

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[1] These data may be obtained directly from the RMA web site at www.act.fcic.usda.gov.

[2] An area for extension of this research is to improve the specification of these variables.

[3] The loss ratio is calculated as total premiums divided by total indemnities. Under actuarially sound rate setting, the loss ratio should be close to one in the long run. The loss ratio minus one represents indemnity payments in excess of premiums, expressed as a share of premiums. "Buy Up" insurance is a catch-all term used to describe all coverage levels above the minimum catastrophic level of 50-percent yield coverage at 55-percent price election. Premiums for catastrophic coverage receive a 100-percent federal premium subsidy and are available for a small processing fee. Greater risk sharing occurs at higher "buy up" coverage levels.

estimated net underwriting losses/gains and administrative/delivery reimbursements. The crop-specific state-level subsidies were then aggregated to the regional level where they were converted to a per-unit basis by dividing by the 1995-98 average production. Table 1 provides a summary of total subsidies, production, and per-unit subsidies for each of the eight crops within each of the seven regions. Clearly, substantial variation exists across crops and regions in terms of per unit subsidies. When national average per unit subsidies are expressed as a percent of projected 1998/99 season average farm prices (SAFP's) the differences become even more extreme (figure 3). The cotton average per unit subsidy of $0.046/pound translates into a 7.5-percent SAFP share compared with about a 1-percent share for rice's $0.051/cwt.

The impact of the crop insurance program is analyzed through the POLYSYS-ERS simulation model jointly developed by ERS and the Agricultural Policy Analysis Center (APAC), University of Tennessee. POLYSYS is designed to anchor its analysis to a baseline of projections for all model variables and to generate simulation results on commodity supply, demand, ending stocks, prices, net returns and Government payments (Ray, *et al*). The POLYSYS-ERS simulation model replaces the linear programming supply component of POLYSYS with one driven by regional supply elasticities and solves for market clearing prices, which adjust the baseline numbers via a set of price flexibility functions (Lin, *et al*). POLYSYS-ERS simulates market behavior for 8 crops (corn, grain sorghum, barley, oats, wheat, soybeans, rice and cotton). Crop production is modeled in 7 production regions (figure 2). The simulation analysis makes use of the same demand components embedded in POLYSYS.

The impact of the Federal crop insurance program is determined by comparing the base scenario (the February 1999 USDA baseline) with and without the insurance subsidies. Insurance subsidies are introduced into the production decision as commodity- and region-specific price wedges. Farmers respond to lagged farm prices as expected prices plus an insurance price wedge when determining planted acreage. Since the baseline implicitly includes the effects of the insurance programs, the price wedges are subtracted to estimate what production and prices would have been in the absence of the subsidies.

Research Limitations

The empirical analysis reported in the remainder of this paper should be viewed as indicative of the effects of the current crop insurance program. A number of serious methodological limitations permeate this undertaking and likely cloud the results and their interpretation. The principal shortcomings are briefly described as a context for appreciating the implications of reported results.

First, treating FCIC subsidies as a single price wedge assumes that producers view the full crop insurance subsidy as increased market revenue. To the extent that administrative/delivery reimbursements and net underwriting losses do not accrue directly to farmers and, as a consequence, farmers do not respond to the full subsidies, the analysis may overstate the influence of crop insurance subsidies on supply response. The estimated production and price impacts would be lower if the full dollar value of the subsidy is not reflected in farm-level decision making.

Second, this study assumes that the 1995-98 period represents historic levels of crop and regional benefits associated with subsidized crop insurance. However, a review of the data suggest that the 1995-98 period was associated with relatively few extreme weather events in the major field crop producing regions and may, as a result, understate the true expected subsidy levels for many regions. Future estimates could be improved by adopting a longer historical perspective.

Third, the elasticities used in the POLYSYS-ERS model are estimated as short-run elasticities. Although the simulation experiment is run over time to permit the sector to adjust to an equilibrium with and without the subsidies, some longer run impacts may not be fully accounted for in the analysis.

Fourth, use of a national level model, such as POLYSYS-ERS, can not account for the array of decisions that individual farmers make in response to risk and programs such as crop insurance. Several aggregation issues arise from such a model including the following three.

- The subsidy price wedge is calculated as an average dollar value per unit of output across all production, when in fact not all farmers use crop insurance. This understates the per unit subsidy that individual farmers using crop insurance actually respond to, and since subsidy effects are assumed to occur at the margin where insurance participation tends to be higher, likely understates the effect of subsidized crop insurance on aggregate production. However, since the subsidy is applied to uninsured production the bias is partially offset.

- By using an average subsidy price wedge for a region, the study ignores subsidy differences based on coverage levels. This may actually produce

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misleading conclusions about the per unit subsidies for differing regions; however the net impact of this assumption on aggregate production cannot be determined with available information.

- By using an average regional subsidy per unit of production, the study overstates the response of low risk farmers (by suggesting that they face a greater subsidy benefit than is true) and understates the response of high risk farmers (by understating their subsidy). Furthermore, higher risk farms likely have lower yields than low risk farms which means that their true "per unit" subsidy is further understated. Again, the net impact of this assumption is indeterminate.

Impacts of Crop Insurance on the Agricultural Sector

While a regional subsidy by crop is a relatively aggregate measure of the incentives created by insurance programs, this approach, nevertheless, provides important insights into production and price implications associated with crop insurance.

The availability of subsidized crop insurance affects farmers' current crop production decisions by creating a direct incentive to expand production. A typical farmer might base such planting decisions on a comparison of the expected net returns from producing alternative crops, such as corn and soybeans. During the 1995-98 period, crop insurance provided an average subsidy of $0.04 per bushel for corn and $0.09 per bushel for soybeans (table 1). With no land constraint, the farmer would be expected to increase production of both crops in response to the subsidies. With a land constraint, the farmer would likely alter each crop's share of acreage in accordance with the changes in their expected net returns induced by the insurance subsidy.

As individual farmers increase or shift acreage in response to the different subsidy price wedges, production and stocks also increase. Farmers will alter their production decisions in following periods in response to the new price levels. As a result of this feedback price effect, production will shift across commodities and regions. Consumers will also adjust their demand in response to the price changes. Over time, these feedback adjustments tend to moderate the aggregate acreage response to crop insurance.

Since the per unit value of insurance subsidies varies across regions and commodities, the long-run effects of the program on regional production patterns and commodity specific impacts, inclusive of these feedback effects, are evaluated by simulating the impacts of the insurance subsidies over a ten-year horizon. Average results representing years 5 to10 are discussed. In addition, aggregate impacts on net income and trade are discussed.

Aggregate Impacts for the 8 Major Crops

For commodities where net acreage increases, stocks build modestly over time dampening prices and moderating the longer-term impact on acreage. Lower market prices also lead to changes in product use. In addition, production adjusts in response to cross-price effects in related markets (recall that all 8 crops receive some level of crop insurance subsidy).

As a result, the estimated net impact on aggregate crop production and prices is relatively small once feedback effects are allowed to stabilize. An average annual FCIC subsidy of $1.4 billion devoted to production of the 8 field crops translates into a net aggregate acreage increase of approximately 600,000 acres (a 0.2 percent increase), while reducing prices for most commodities by less than 1 percent. The initial impacts (in the first year) of introducing subsidized insurance are somewhat larger with acreage expanding by about 1.0 million acres in the first year. But importantly, the modest 0.2 percent increase in long-run planted acreage masks somewhat larger commodity and regional impacts.

Commodity Impacts for the 8 Major Crops

The insurance subsidies induce increased production for six of the eight major crops (figure 4). The subsidy impacts differ in response to direct and cross-price effects. The largest initial impact occurs for wheat with area increasing by 870,000 acres in the first year, a 1.6-percent increase. In subsequent years, wheat area responds to lower wheat prices combined with cross price impacts from competing crops to reduce wheat acreage as the sector approaches equilibrium. After several years the increase in wheat area averages only about 330,000 acres over baseline levels and wheat prices stabilize at about 1 percent lower. Wheat acreage impacts vary across regions–production increases in the Plains and North Central regions are partially offset by small declines in the Southeast and Far West regions.

The largest long-run impact in relative terms, however, occurs for cotton with annual acreage planted expanding by 1.2 percent (160,000 acres). As a percentage of price, the per unit value of the insurance subsidies is also largest for cotton. Cotton insurance subsidies averaged $0.043 per pound, or almost 9 percent of the season average farm price received, during the 1995 - 1998 time period.

At 72,000 additional acres planted, long-run annual average corn production expands more than any crop except for wheat and cotton. However, this increased area represents a relatively small portion of total corn area (0.1 percent).

Rice and soybean long-run acreage appears to decline modestly in response to the crop insurance program. Historically, the crop insurance program for these two commodities have been more actuarially sound than most other crops, although this has varied by region. A relatively higher per unit subsidy value for soybean production in the Delta states leads to a modest increase in production which is offset by an equivalent decline in the Southeastern states. The increased relative profitability of soybean production in the Delta states draws about 10,000 acres out of rice production. The decreased rice production in the Delta is partially offset with increased production in the Southern Plains and Far Western states. Nevertheless, the net impact is a small reduction in rice production accompanied with a 0.1 percent increase in prices.

For grain sorghum, insurance subsidies draw production out of the Central and Northern Plains region into the Southern Plains region. The average grain sorghum subsidy is $0.25 per bushel in the Southern Plains region compared to less than $0.05 in other regions.

Regional Production Patterns

The impact of FCIC subsidies becomes more evident when regional production patterns are examined (figure 5). Regional acreage adjustments reflect differences in commodity insurance subsidies across regions and differences in commodity response in POLYSYS-ERS. Over 70 percent of the national increase in planted area attributable to crop insurance subsidies occurs in the Southern Plains region, even though it contains only 10 percent of the nation's cropland. Production also increases in the Central and Northern Plains and the North Central regions, while acreage declines in the Southeast and Far West regions.

The average per unit value of insurance subsidies is considerably higher in the Southern Plains, reflecting the higher risk in this region compared to other regions of the country. Per unit subsidies for wheat, upland cotton, corn, grain sorghum, and soybeans are highest in the Southern Plains region. The higher per unit value of subsidies induces a 1.6 percent increase in planted area in the Southern Plains in response to the insurance programs. Wheat and cotton account for most of the increase. About two-thirds of the national increase in wheat and cotton acreage is in the region.

The second largest acreage adjustment occurs in the Central and Northern Plains region where FCIC subsidies draw about 165,000 acres into production. Most of the increase is wheat; however, feed grain production also increases marginally, with the exception of grain sorghum. As mentioned previously, federal insurance subsidies encourage a shift in grain sorghum production from the Central and Northern Plains region to the Southern Plains. In the North Central region, wheat and corn production increase while soybean production declines in response to the program.

Aggregate production in the Southeast is lower than it otherwise would be as a result of the insurance program. Wheat area declines by 1.3 percent. This decline can be attributed to the relatively lower per unit value of insurance subsidies in the region combined with a response to the lower national-level wheat prices. Soybean production declines primarily in response to the relatively lower regional subsidy. Cotton acreage increases. While the cotton crop insurance subsidy is lower in the Southeast ($0.031/pound) than in the Southern Plains ($0.111/pound), the subsidy is sufficiently high to encourage a 1.0 percent increase in cotton area.

Net Returns

Subsidized crop insurance enhances net returns to farmers by lowering the costs of participating in the insurance program. However, all of the subsidy does not accrue to producers since the insurance program induces increased crop production and thus lower prices. In spite of increased crop production, cash receipts for crop production decline by $210 million in response to the lower prices. Additionally, variable costs of production increase by about $85 million due to the increased planted area. The net effect of combined higher costs and lower cash receipts is that a $1.4 billion payout in annual crop insurance subsidies increases net farm income from crop production by less than $1.2 billion annually.

Lower crop prices also induce a spillover effect in the livestock market. Livestock production increases in response to the lower feed costs. Increased livestock supplies depress market prices somewhat. Livestock cash receipts drop by approximately $23 million.

Trade

Crop insurance subsidies appear to have a small impact on trade, as measured by U.S. exports (figure 6). The largest relative distortions occur for cotton where exports are projected to increase by 2.0 percent in response to the subsidies. Wheat, corn and barley exports increase

moderately, while rice exports decline. With the exception of cotton exports, the current crop insurance program does not appear to significantly distort trade.

Government Costs

Government subsidies for insurance translate directly into program costs. Although not explored in this analysis, FCIC subsidies could have a secondary impact on government costs. This analysis indicates that insurance programs lead to reductions in prices and cash receipts. In years such as 1998 and 1999, when commodity markets are weak, an additional reduction in commodity prices increases budgetary exposure from marketing loans and loan deficiency payments, particularly for cotton and wheat. In addition, the increased cotton production, and subsequent exports, attributable to the program can lead to higher costs for the cotton step 2 payment program.

Concluding Remarks

The results reported here should be viewed as indicative of the impacts of FCIC crop insurance subsidies on commodity production and prices. This analysis treats federal insurance subsidies as explicit price gains available to all producers. Obviously, not all farmers respond to such a price incentive in the same manner. Participation in crop and revenue insurance represented about 61 percent of eligible acres in 1998 indicating that a large share of producers chose to ignore the subsidy incentive. And while the subsidy creates an income transfer, not all farmers seek to maximize such subsidy transfers. Instead many producers base their insurance and production decisions on a combination of risk management and farm returns objectives.

Many of the subtleties of insurance and insurance products are not captured in our aggregate subsidy wedge. Use of an aggregate subsidy masks individual decision making and glosses over the differences in risk aversion known to exist at the farm level. In addition, use of an average price wedge likely understates the true subsidy incentive faced by those farmers with riskier land that tend to participate in the program. These influences indicate a potential for the POLYSIS-ERS approach to underestimate the impacts of insurance on production and prices.

Nevertheless, in spite of these and other shortcomings, this preliminary look at the potential for commodity market distortions via an aggregate model, when viewed in combination with micro level analyses, enriches our understanding of how insurance subsidies may affect production decisions.

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Table 1– Government crop insurance subsidies by production region for major field crops, annual average during 1995-98.

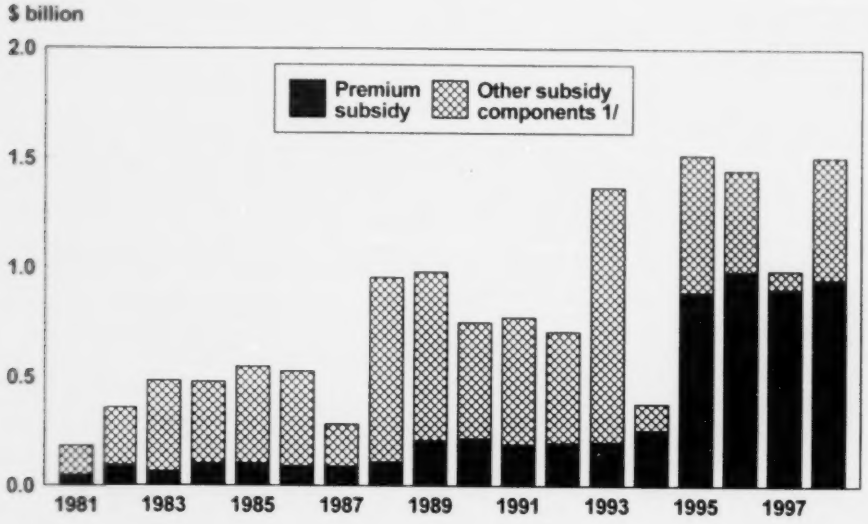
Region	Wheat	Oats	Rice	Upland Cotton	Corn	Grain Sorghum	Soybeans	Barley	Total 4/
Federal Subsidy				$ Million					
Northeast	0.3	0.0	—	—	8.0	0.0	2.4	0.0	10.8
Southeast	4.2	0.0	7.6	69.0	19.8	0.1	15.9	0.1	109.2
Delta	4.9	0.0	7.6	36.7	6.4	1.1	32.2	—	89.0
N Central	33.3	1.1	0.3	2.3	212.5	1.6	111.1	3.3	365.6
C & N Plains	213.3	3.8	—	0.1	104.4	17.2	55.0	19.9	413.8
S Plains	56.5	0.2	—	253.6	27.4	44.3	4.3	0.0	386.4
Far West	11.2	0.1	1.2	9.4	0.9	0.0	—	1.6	24.4
Total 1/	323.8	5.3	9.1	371.2	379.5	64.5	220.9	25.0	1,399.2
Production	Mln bu.		Mln cwt	Mln lbs	Mln bu.				
Northeast	36.2	16.3	—	—	252.1	—	38.6	11.4	—
Southeast	113.3	5.3	—	2,258.3	387.4	5.1	153.6	7.7	—
Delta	61.9	0.8	119.3	2,074.3	110.1	22.9	180.7	—	—
N Central	337.2	68.7	6.2	242.3	5,850.2	47.8	1,769.7	32.0	—
C & N Plains	1,174.6	55.0	—	3.3	1,977.0	349.3	342.7	195.0	—
S Plains	250.6	6.6	16.6	2,202.7	247.4	176.7	14.8	0.5	—
Far West	399.2	9.4	37.0	1,325.1	76.0	—	—	119.5	—
Total 2/	2,373.0	162.2	179.1	8,106.0	8,900.1	601.9	2,500.0	366.0	—
Per Unit Subsidy	$/bu.		$/cwt	$/lbs	$/bu.				
Northeast	0.008	0.002	—	—	0.032	—	0.062	0.004	—
Southeast	0.037	0.008	—	0.031	0.051	0.024	0.103	0.012	—
Delta	0.079	0.025	0.064	0.018	0.058	0.050	0.178	—	—
N Central	0.099	0.016	0.052	0.010	0.036	0.034	0.063	0.103	—
C & N Plains	0.182	0.070	—	0.030	0.053	0.049	0.160	0.102	—
S Plains	0.226	0.034	—	0.115	0.111	0.251	0.290	0.079	—
Far West	0.028	0.006	0.031	0.007	0.012	—	—	0.014	—
Average 3/	0.136	0.033	0.051	0.046	0.043	0.107	0.088	0.068	—

"—" implies no appreciable values. 1/ Total Subsidy = premium subsidy plus share of subsidized administrative and delviery costs and net underwriting losses. The latter are calculated as the loss ratio minus one times the premium subsidy on buy-up coverage. Calculated from RMA/USDA data. 2/ Calculated from NASS/USDA data. 3/ Dollars per bushel for wheat, oats, corn, sorghum, soybeans, and barley; dollars per pound for cotton; and dollars per cwt for rice. 4/ Sum across the eight field crops listed. Totals are only relevant for subsidy values since production units vary.

Source: Economic Research Service, USDA.

Figure 1

Federal Crop Insurance Subsidies, 1981-98



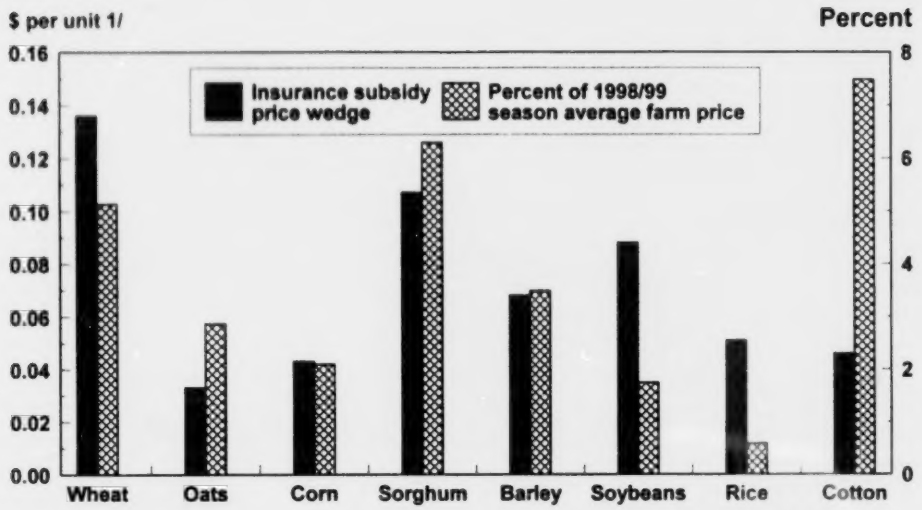
1/ Other subsidy includes reimbursement for administrative and delivery costs, as well as government share of net underwriting losses and excess loss payments.
Source: Risk Management Agency, USDA

Figure 2

U.S. Crop Production Regions

Figure 3

Commodity Level Subsidies

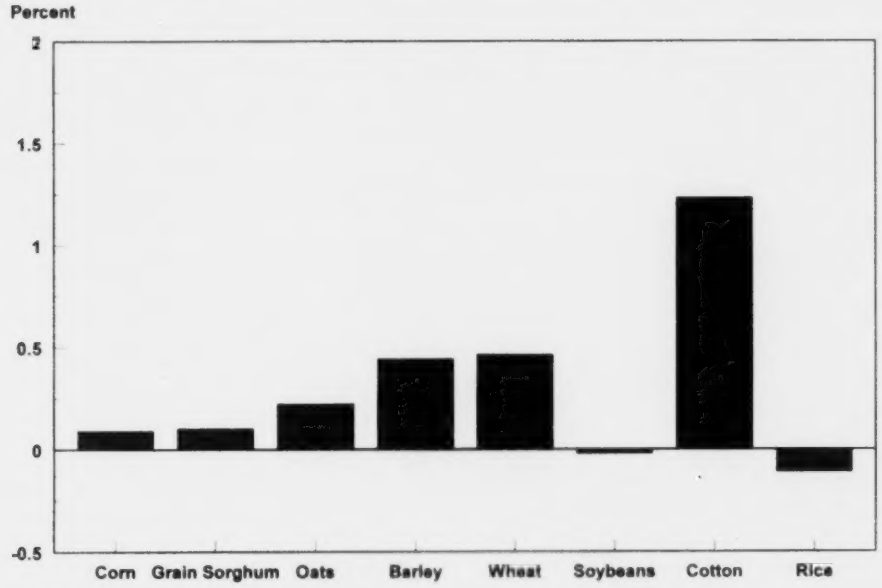


1/ $ per bushel for wheat, oats, corn, sorghum, barley, and soybeans; $ per hundredweight for rice, and $ per pound for cotton.

Source: Calculated from Risk Management Agency, USDA data by Economic Research Service, USDA

Figure 4

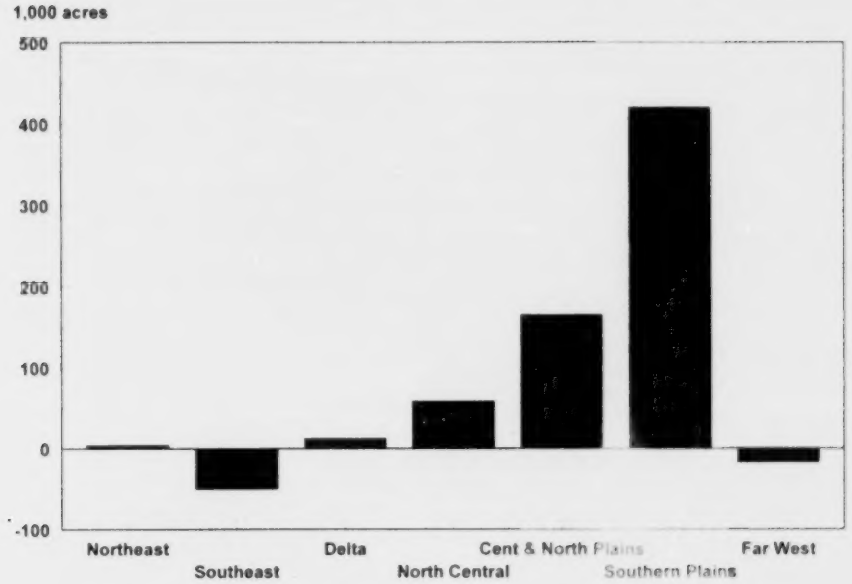
Percent Change In Acreage Impacts By Commodity



Source: Economic Research Service, USDA

Figure 5

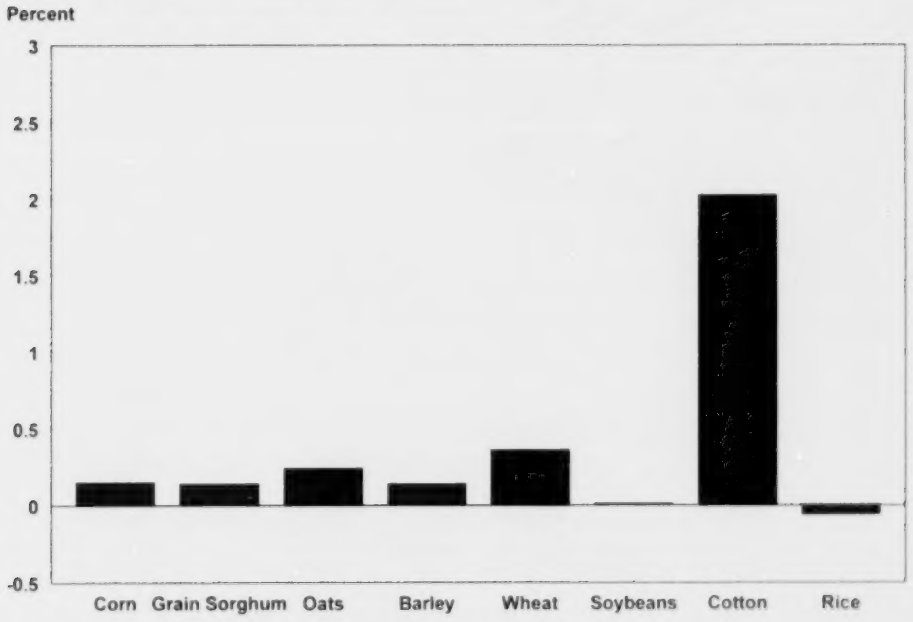
Estimated Regional Acreage Impacts



Source: Economic Research Service, USDA

Figure 6

Percent Change In Trade By Commodity



Source: Economic Research Service, USDA

Concurrent Sessions II

Y2K FORECASTS FROM DENIAL TO DOOMSDAY

Chair: Tim Mack
AAI Research and Futures Research Quarterly, World Future Society

Panelists:

Margaret Anderson
Y2K and Society Project

Kenneth W. Hunter
World Future Society

Farms, Food and Y2K: Aiming for a Safe, Reliable, Abundant, Affordable Food Supply,
Janet E. Perry, Economic Research Service, U.S. Department of Agriculture

Y2K Forecasts from Denial to Doomsday

Chair: Tim Mack
AAI Research and Futures Research Quarterly, World Future Society

Assessing Y2K--year 2000--conditions, the progress being made, and the likely impacts is now a challenge facing individuals, organizations, businesses, and governments. While many remain in denial, others are learning on the go and altering their forecasts daily. Yet others are seriously concerned about disasters, and the doomsayers are using this as an opportunity. This session will provide reports from people directly involved in making assessments and advising on Y2K strategies. The scope of the work includes forecasting for complex socio-economic-technological emergencies, emergency management and contingency planning processes, technology impacts, and understanding how socio-economic groups and systems will respond and change during and after the Y2K events. Scenarios are being used extensively in this analysis.

Panelists:

Margaret Anderson
Y2K and Society Project

Janet Perry
Economic Research Service, U.S. Department of Agriculture

Kenneth W. Hunter
World Future Society

FARMS, FOOD AND Y2K: AIMING FOR A SAFE, RELIABLE, ABUNDANT, AFFORDABLE FOOD SUPPLY

Janet E. Perry
USDA Economic Research Service

The U.S. food supply chain is a large and complex web. Food production, distribution and marketing account for a fifth of the Nation's GDP. It involves millions of people-- from those supplying inputs to the production process, to farmers, processors, wholesalers and distributors, retailers and restaurants. The sector also includes workers in the importing and exporting of food and fiber.

Trade plays a vital role in the agricultural sector. Exports are a large, important market and much of the food produced in this country is consumed overseas. Production equivalent to one out of three acres is exported. Imports add variety to American's diet, especially in fresh fruits and vegetables and especially in the first few months of the year when effects of Y2K may be strongest.

Secretary Glickman, in his testimony to Congress on February 4, 1999, indicated that USDA has two goals with regard to the so-called "Y2K problem," where computerized equipment may not function properly when the year rolls over to 2000. First, assure that consumers have reliable access at reasonable prices to basic foodstuffs, the safety of which has not been compromised. And second, assure that farmers have the capability to sustain production and to move commodities to market. The Food Supply Working Group is chaired by the Department of Agriculture. The Group is part of the President's Council on Year 2000 Conversion, and has spent a great deal of energy trying to answer questions about Y2K problems as they relate to the Nation's food supply.

The Food Supply Working Group is co-chaired by the Under Secretaries for Food Safety, Farm and Foreign Agricultural Services, and Marketing and Regulatory Programs. It includes representatives from the Departments of State, Health and Human Services, Defense, and the Commodity Futures Trading Commission. The working group also includes representatives from USDA agencies whose activities sustain the food supply. All of USDA's agencies are reaching out to their constituents to raise their awareness of the problem.

Using knowledge about how food moves from farm to table, attention was focused on the links in the supply chain that produce and distribute food. Whether it is the household, processing firm, or farm operation, inputs must arrive as needed, internal production processes should function properly; and output needs to be delivered to the next part of the chain. Knowledge of the production and distribution networks about the most vulnerable types of agricultural products allows us to pinpoint the links susceptible to Y2K problems. The key is to find the links that have both a high probability of failure or serious malfunction due to a Y2K problem, and serious adverse consequence for food security if the link were to fail or malfunction.

Individuals and households consume food at home or in retail outlets away from home. ERS estimates that $320.3 billion of the $714.9 billion American's spent for food was for food consumed outside the home (Clauson). But whether the food is prepared and consumed in the home or served in a restaurant, for Y2K there are similar concerns about the distribution chain.

Food can be divided into two categories. Non-perishables are foods that do not require temperature control and that have indefinite shelf life, including canned and dry goods. Perishables are foods that require temperature control and/or have limited shelf life, including fruits and vegetables, dairy, meat and fish, baked good, and frozen foods.

Three categories of linkages might be vulnerable to computer problems such as Y2K. First, inputs must be delivered. Some inputs such as feed for livestock, seed for crops, machinery, fuels and non-perishable inventories are storable. Other inputs such as water, labor, electricity, and perishable inputs or food products are not storable, and must be delivered according to a schedule. Each group may have exposed positions if storage or delivery relies computerized equipment. So, the second linkage is that the production processes must work properly. Examples of these processes are environmental controls for livestock, milk products and grain storage systems, machinery and equipment for input and food handling. Finally, inputs and output must be delivered. Delivery may include linkages to communications and tracking systems, and the transportation and storage industries.

At first glance potential vulnerabilities may exist. Small and medium sized food companies appear less prepared than larger ones. Concentrated food industry segments may be more vulnerable than dispersed segments. Perishable inputs and foodstuffs are less resilient than non-perishables and firms relying on them could find production or service difficult if Y2K problems disrupt distribution. Because trade is so important to U.S. agriculture, concern exists for some sectors abroad that are not fully engaged in Y2K activities. The Asian financial crisis potentially has drained resources away from fixing computer problems. And, political difficulties in Europe may have diverted attention from Y2K. Emerging market counties may not have the necessary human capital to deal with any computer issues.

However, according to the Food Supply Working Group, any problems that arise likely will be splintered, minor, and temporary. The system's diversity contributes to its robustness. Most firms distributing food in the United States and overseas have assured USDA that they are becoming Y2K ready. The largest companies have the resources and reason to address the problem. And, larger companies are asking for assessments from their smaller partners--in some cases, assisting in remediation and testing.

The agriculture sector's size and diversity will alleviate potential gaps. The numerous producers, delivery channels, and delivery points make it unlikely that all these components could fail simultaneously and cause an industry-wide collapse. Market forces will ensure that any gap is rapidly filled by more prepared competitors.

One group that USDA did not have much information on the primary producers of basic food commodities. The Department needed an assessment of the Y2K problems faced by farmers. The Research, Education and Extension Mission Area of the Department was asked to design a method to assess whether these primary producers of food were vulnerable. The National Agricultural Statistics Service then implemented a telephone survey of producers in December 1998. The goal of the survey was to identify potentially vulnerable systems, determine farmers' awareness of potential problems, determine Y2K compliance levels, and to estimate costs of repair to necessary equipment.

The dataset contains 1,143 samples representing farmers across the county. Respondents were sampled to represent all sizes of farms (small farms with sales less than $250,000 and larger farms--Table 1) and commodity groups (cash grains, specialty crops, other crops, and livestock—Table 2). Official estimates of the number of farms in 1998 was 2.1million and this survey represents 1.8 million.

Using a rubic that determines compliance level, ERS found that over 80 percent of farmers have heard about the concern known as the Y2K problem, where if changes aren't made, some computers and computer-based equipment might not work correctly on January 1, 2000 Six percent of farmers considered themselves fully compliant and 15 percent were making progress towards compliance. Sixty percent were aware that Y2K problems might exist, but hadn't begun working on the problems. Of those that were aware of possible problems, two-thirds knew that computer problems could exist in farm machinery, irrigation systems, feeding systems and environmental controls.

An inventory was taken of the types of equipment systems (other than a personal computer) that might have problems (Table 3). Just over 30 percent of the farmers surveyed said that they had some of the listed equipment and this group was much more likely to be aware of Y2K problems. Ninety-three percent of farmers with heating/cooling or ventilation systems and 82 percent of those with geographic positioning systems (GPS) were aware of possible problems. Farmers using computers for bookkeeping purposes (75%) and those with other computerized systems that might have problems (79% - 55%) were aware of the Y2K problems. Full compliance for farmers having the above systems ranged from 20 percent to 34 percent. For farmers having any of the other systems (irrigation, feeding, milk storage, and any other systems), awareness of Y2K was higher than those without one of the listed systems, and full compliance ranged from six to 20 percent.

Farmers with larger operations farms (sales over $250,000) were more aware of potential problems and more likely to be compliant or moving towards compliance. But, operators of small farms had reasons not to be aware. While one in five farmers were NOT aware of problems associated with Y2K, most of these respondents did not have systems that could be affected. Almost all were very small livestock operations—with a few head of livestock on pasture. On larger farms (sales over $250,000) only 12 percent were NOT aware of possible problems, and again, these farmers were less likely to have machinery or equipment considered vulnerable to Y2K problems.

Farmers' estimates to fix problems were low. Of farmers who have either fixed or are attempting to fix Y2K problems, 54 percent indicated costs estimates of $1,000 or less. Because larger farms have more

complex systems, costs were more on larger farms. About half of the large farm operators said their costs to mitigate problems would range between $1,000 and $4,999. Four percent indicated costs might exceed $5,000.

Farmers need to consider vulnerabilities of the upstream activities that make inputs available and the interface with the off-farm processing and distribution networks as well as the on-farm production process. A final question asked farmers if they had contacted suppliers, service providers, market outlets, financial advisors or their insurance companies about Y2K compliance. About 14 percent of all farmers had done this, with large farm operators and those of any size specializing in cash grains being most likely to have contracted suppliers, distributors, or service providers.

Serious interruptions in the US food supply are unlikely and operations likely continue despite any temporary interruptions due to Y2K problems. Most firms in the supply chain with the potential to be affected are, or are becoming, Y2K ready. No major disruptions are expected and any minor ones likely will be resolved quickly. The system's size and diversity will alleviate gaps due to Y2K interruptions.

Since our preliminary assessment shows an encouraging state of readiness, the key then is communication. Information is the antidote to panic and profiteering. Needless and frivolous stockpiling could strain reserves and create isolated shortages before Y2K arrives. USDA is using existing knowledge about food and agricultural systems to assist in a smooth transition. Secretary Glickman has testified in hearings on the Hill last February; USDA has Y2K information on their homepage (www.usda.gov) and plans to have continued assessment. The field offices of the Cooperative State Research, Education, and Extension Service are distributing fliers designed to make farmers aware of possible problems due to Y2K, and to help develop skills to ameliorate computer problems. Other USDA agencies have similar programs.

In Secretary Glickman testimony before Senator Bennett's committee in early February, he pointed out that "the state of readiness of the food industry is encouraging. ... an interruption in the food supply so severe as to threaten the well-being and basic comfort of the American public is highly unlikely."

The Secretary noted-- and the Food Supply Working Group and President's Council on Year 2000 Conversion agree-- that it just makes good sense to have some extra supplies on hand during winter months in case there is a weather related emergency, not just for Y2K. People should be prepared just as they would be if they expected a winter storm.

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Table 1. Compliance level by size of farm, 1998			
Compliance Level	Small farms	Large farms	All farms
Fully compliant	5.5	10.5	5.9
Becoming compliant	14.6	21.7	15.1
Aware of problem	60.3	55.4	60.0
Not aware of problem	19.6	12.4	19.1
Percent of farms	92.8	7.2	100.0
Source: Compiled by ERS from USDA-NASS telephone survey of farmers, December 1998.			

Table 2. Compliance level by type of farm, 1998					
Compliance Level	Cash grains	Specialty crops	Other crops	Livestock	All farms
Fully compliant	9.0	3.3	2.2	5.8	5.9
Becoming compliant	18.3	24.8	14.7	14.1	15.1
Aware of problem	55.0	56.1	61.3	61.0	60.0
Not aware of problem	17.8	15.8	21.9	19.1	19.1
Percent of farms	15.4	3.0	9.2	72.4	100.0
Source: Compiled by ERS from USDA-NASS telephone survey of farmers, December 1998.					

Table 3. Compliance level by type of equipment, 1998			
Compliance Level	Had equipment	No listed equipment	All farms
Fully compliant	16.2	1.1	5.9
Becoming compliant	32.0	7.3	15.1
Aware of problem	46.0	66.4	60.0
Not aware of problem	5.8	25.2	19.1
Percent of farms	32.7	68.3	100.0
Source: Compiled by ERS from USDA-NASS telephone survey of farmers, December 1998.			

ECONOMIC FORECASTING ISSUES: POPULATION AND LABOR FORCE

Chair: Norman C. Saunders
Bureau of Labor Statistics, U.S. Department of Labor

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Contingent Forecasting of the Proportion with Small Incomes in a Vulnerable Nonmetro Population,
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Is Nonmetro Unemployment Stationary?: A New Look

David Torgerson, Economic Research Service of USDA

Summary

Standard stationarity tests indicate that while nonmetro and metro unemployment rates are not stationary, the respective cyclical unemployment rates are stationary. These results suggest further exploration of forecasting techniques involving independent estimates of trend nonmetro unemployment rates combined with time series techniques for short-range forecasting. The differences in the stationarity properties of the metro and nonmetro unemployment rate series suggest caution in combining these series in a forecasting or policy model. The stationarity differences are pronounced in the cyclical unemployment rates, consistent with the view that the nonmetro and metro labor markets respond to business cycles differently.

The Importance of Non-metro Unemployment

The nonmetro unemployment rate is important both for its role in the general economy and as a relative indicator of the economic state of rural America. Currently, the nonmetro labor is about 20 percent of the U.S. labor force. The nonmetro unemployment rate is one of the few indicators of rural well-being available in a timely manner, and as such, has become important to policymakers concerned with rural development. The nonmetro unemployment rate exceeded the metro unemployment rate throughout the 1983-1989 economic recovery. The current expansion, starting in 1991, has seen the metro and nonmetro unemployment rates converge.

Despite the importance of this area, relatively little work has been done in looking at nonmetro unemployment issues. An Internet search revealed only two works on rural unemployment, compared to hundreds on the general unemployment picture. Nevertheless, at the Eighth Federal Forecasters Conference Hamrick (1996) presented a paper detailing the importance of the rural unemployment rate and examining some of the time series properties of the rural unemployment rate.

This paper extends Hamrick (1996) in three ways: (1) the data series used here is more current, ending in 1998, (2) the metro unemployment rate is compared to the nonmetro rate directly, and (3) a modern filtering technique is used to separate cyclical from trend effects. Updating time series improves the relevance of statistical testing. Hamrick focused on developing a forecasting system for nonmetro unemployment rates, this work seeks to compare and contrast metro and nonmetro unemployment rates. Finally, the emergence of real business cycle theory has made for widespread availability of filtering techniques such as the Hodrick Prescott filter. The implementation of this filtering technique used is in Eviews 3.1 (See http://www.eviews.com/general/qmsprod.html). This technique allows one to separate the cyclical and structural unemployment components in metro and nonmetro unemployment rates.

Why Test Stationarity?

Testing stationarity of the nonmetro unemployment rate is central to deciding if the unemployment rate is forecastable. A rough definition of forecastablity is that error in a forecast of the variable in question is lower on average for shorter forecast horizons. If a series and /or its explanatory variables are not stationary then forecasting models are often unstable. The ignored instability translates in practice into making apparently good forecasting models perform poorly out-of-sample (Diebold and the Lutz (1999)). Stationarity testing is often a first step in developing a forecasting model.

Secondly, the stationarity tests allow a comparison of two related series. If the metro and nonmetro unemployment rates have different stationarity properties, then that would strongly suggest some important structural differences. The nonmetro areas have borne the burdens of the recessions and have enjoyed the fruits of recovery differently then metro areas. The past three recessions and recoveries showed very different employment growth patterns in metro and nonmetro areas indicating the possibility of different time series properties. Economic Research Service (ERS) research indicates that nonmetro employment is much more dependent on the international economy than the metro areas economy. (See Hamrick(1996). A disproportionate share of rural employment is tied to manufacturing and agriculture. (Torgerson and Hamrick (forthcoming).) Goods exports are the growth markets for agriculture and manufacturing. So goods exports, and the variables influencing U.S. goods exports, have a disproportionate impact on rural employment.

In particular, world growth drives U.S. goods export growth, and a strong dollar slows goods exports growth. Weak world growth and the strong dollar from the Asia crisis have had relatively more impact on nonmetro than metro employment. (Torgerson and Hamrick (forthcoming).) Hence, it is reasonable to examine the stationarity properties of nonmetro unemployment rates and compare them with metro unemployment rates as they well might behave quite differently.

The unemployment data for nonmetro and metro areas begin in 1974 quarter 1 and end in 1998 quarter 4. The series are produced by the Bureau of Labor Statistics and seasonally adjusted by the Economic Research Service.

Over much of the period of empirical econometrics since World War II, the time series attributes of economic data have been largely ignored or incorrectly assumed. Nelson and Plosser (1982) claimed the vast majority of empirical macroeconomic econometric results were invalid since they implicitly assumed that macroeconomic data were stationary when they were generally not. A time series without stationarity potentially invalidates statistical analyses testing economic theories as well as the implied stability of a forecasting equation. A stationery series has a constant mean and a variance/covariance error structure dependent only on the magnitude of differences between time periods. Without this property, time series data coefficient estimates are more variable than reported by statistical package, significance tests are invalid, and forecasting out-of-sample is problematic.

Nonstationary series are also subject to the spurious regression problem. See Granger et al (1987). The spurious regression consists of two series apparently related significantly as in a regression equation. If these series are two random walks using one to forecast the other could result in a large forecast error out of sample. Consider nonmetro unemployment as the variable to be forecasted based on the overall unemployment rate. If both series are nonstationary (and are stationary of the same order) and are both related to time, a forecasting regression equation with a time trend term would be reasonable. A short-term forecast is done and the alleged relationship breaks down in forecasts after the estimation sample period. As a result of all these considerations, the stationarity of time series properties of data should be examined.

Nonmetro Unemployment Rates

Do nonmetro and metro unemployment rates differ in terms of stationarity? We expect, given smaller search costs, that the metro unemployment rate should be more stable than nonmetro unemployment rate. Further, the heavy dependence of rural labor markets on goods production as outlined above may make nonmetro unemployment more sensitive to general macroeconomic conditions and the relatively volatile goods exports.

The nonmetro unemployment rate NUR(t) is tested for nonstationary under three related null hypotheses,

The No Constant null hypothesis is:

(1) NUR (t)=NUR (t-1) + e(t), with E(e(t))=0. (Random Walk Hypothesis).

The Constant and Time Trend null hypothesis is:

(2) NUR (t) = NUR (t-1) + constant + a*t + e(t), with E(e(t))=0. (Random Walk plus Drift).

The Constant-only (constant with no time trend) null hypothesis is:

(3) NUR (t) = NUR (t-1) + constant + e(t), with E(e(t))=0.

A nonstationary series can be thought of as being unstable in that if it is not possible to reject at least one of the above hypotheses then the data are inconsistent with stability. First, under the hypothesis NUR has a zero constant mean as in (1) if accepted is known as the Random Walk hypothesis. Secondly, NUR could have a constant mean except for a time trend as in (2) called a Random Walk plus Drift. Thirdly, NUR could have a constant nonzero mean as in (3). For example, in the random walk case of (1), the best forecast is simply the last period's value making all the other information about past history of the NUR useless. In contrast, patterns of past dependence allow macroeconomic variables to be forecasted with some accuracy. Further, the NUR under equation (1) would in principle cycle around and around with out converging to a specific value even though moving around a constant such as in (3). Most economic models presume some kind of equilibrium. An unstable series such as day-to-day stock market prices are indeed difficult to forecast.

The major tests to analyze stationarity are the Augmented Dickey Fuller test (ADF) and the Phillips-

Perron test (PP). Since the ADF and PP use the same null hypotheses ((1), (2), (3)) they differ only in their power functions (how likely a statistical test is to falsely accept the null hypothesis) they are typically both used. Under most but not all cases, the PP is more powerful than the ADF in that it is less likely to accept the null hypothesis if it is false. The PP generally will accept the null hypothesis when it is false less frequently than the ADF. If the nonmetro unemployment rate is indeed not nonstationary then the PP will accept the null hypothesis of nonstationarity less frequently than the ADF will. But since the PP has not been shown to be more powerful in all circumstances both tests are used.

The Strategy

We test for the stationarity of the levels of both the metro and nonmetro unemployment rates. The typical operation is to stop differencing the series as soon as the transformed the series proves to be stationary. The stationary tests often give clues for continuing the model development strategy. For example, if the time trend plus constant case (2) is accepted then a regression model with a time trend could be useful. Of course, the metro unemployment rates are tested under hypotheses completely analogous to equations 1 to 3.

The second stage is to first difference the data if it has been shown to be nonstationary in levels. Much of the macroeconomic data discussed in Nelson and Plosser (1982) become stationary after first differencing. Very volatile financial series require second or third differencing before the transformed series become stationary. Since we are looking at the relative stationarity properties of nonmetro and metro unemployment series we do one more level of differencing than necessary to transform a variable into one which is stationary.

The Results of Stationarity Testing for Measured Unemployment Rates

Table 1 shows that the nonmetro unemployment rate is consistent with nonstationary under all three cases by both the PP and ADF tests, since the test ADF and PP statistics are all less than the critical value with 99 percent confidence. For example, table 1 under the constant-only case has an ADF value of –2.216703, which is less than the critical value of –4.4972. This says that the sample data cannot reject the nonstationarity of the type in equation 3. As in table1, table 4 shows that nonstationarity cannot be rejected for the metro unemployment rate according to both the PP and ADF tests for the metro unemployment rate. The PP statistic for the constant and time trend case is –2.605540 which is less than the –4.0494 one percent critical value so nonstationarity can not be rejected.

Table 1 and 4 give almost identical results. The first-differenced series (NUR (t)-NUR (t-1)) is apparently stationary as the second part of Table 1 shows for all three cases. Table 4 yields similar results for metro unemployment rates using the PPP test. In only the constant plus trend case under ADF, is there an apparent difference with the first difference of metro unemployment being stationary at the 5 percent level but not at the 1- percent level. Given the small sample and the success under the usually more powerful PPP we ignore this difference. Thus, an equation relating first differenced nonmetro and metro unemployment series should contain a time trend time plus a constant, a constant and no time trend, or no constant and a no time trend based on other considerations.

Are filtered nonmetro and metro unemployment rates stationary. A filter attempts to extract the trend from the cyclical part of the series. In the case of unemployment rates, given the validity of real business cycle theory, the appropriately filtered rates are the trend "full employment" or structural plus frictional unemployment rates

Trend Decomposition of Unemployment Rates and Stationarity

The same revolution that addressed shortcomings in empirical Macroeconomics also questioned the Keynesian and Monetarist conceptions of the business cycle. Hodrick and Prescott (1997) invented a filtering technique to separate trend from cycle in macroeconomic time series data. I use the Hodrick Prescott (HP) filter to first see if the trend unemployment rate is stationary and then back out the cyclical unemployment rate as the difference between measured unemployment rate and the filtered trend unemployment rate. I follow Hodrick and Prescott's implicit interpretation that the trend unemployment rate using the HP filter is the NAIRU (non-inflation accelerating unemployment rate). So the difference between the actual unemployment rate and the HP filtered rate is the cyclical unemployment rate. Note, in a boom period the cyclical unemployment rate may be negative as the rural or urban economies may be above full employment.

Table 2 shows that the HP-filtered nonmetro unemployment rate series requires second differencing to make the transformed series stationary according to the ADF for the constant-only and the no constant case.

(The Random Walk plus Drift model can not be made stationary even with second differencing.) Further, the filtered series fails the PP test fails even with second differencing for all cases. The results for the nonmetro unemployment rate are exactly the same (Table 5).

The use of these HP-filtered unemployment rates given the high degree of differencing necessary to make the series stationary under the ADF and the failure of second differencing to make them stationary under the PP tests should make one very cautious in using these series. Even second differenced versions of these series given they failed the PP tests should likely not be used for forecasting. Further, second differencing causes so much information to be lost that the usefulness of using second differenced data for forecasting is usually in doubt even without PP test failure.

Cyclical Unemployment Rates Compared

As table 3 indicates the nonmetro cyclical unemployment rate is stationary in the constant and no constant cases and nonstationary in the random walk plus drift case. Again this is of no great importance, as modeling strategies which do not involve use of a time trend for forecasting are often used. It is interesting that the cyclical nonmetro unemployment rate is stationary while neither the measured or trend unemployment rates are.

The cyclical metro unemployment rate is stationary only in the case of no constant (and no trend) as seen in table 6. As the no constant case is the least useful for forecasting it would be unlikely in practice one would want to combine the cyclical metro and nonmetro unemployment rates. Further, one would have a difficult time linking a differenced metro unemployment rate with a level nonmetro unemployment rate.

Conclusions

The reported metro and nonmetro unemployment rates are nonstationary. The HP-filtered trend unemployment rates are nonstationary as well. But the cyclical unemployment rates for both metro and nonmetro areas are stationary in the no constant case. In the more useful, constant-only case the nonmetro cyclical unemployment rate is stationary as well. This suggests that an independent estimate of trend nonmetro unemployment rates, such as one derived as residual from employment and unemployment equations, combined with the cyclical estimate obtained here, could make for a reasonable forecasting system for nonmetro unemployment rates. That topic is the subject for further analysis.

The discrepancy between the stationarity properties for the cyclical nonmetro and metro unemployment rates is consistent with the view that the business cycle effects on nonmetro unemployment compared to metro unemployment has been quite different. (See Torgerson and Hamrick (forthcoming).)

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Table 1 Nonmetro Unemployment Rate Unit Root Tests for Nonstationarity

Unit root level testing:

	ADF Statistic	**1%Critical Value***
No constant	-0.437988	-2.5866
Constant and Trend	-2.683789	-4.0530
Constant-only	-2.216703	-3.4972
	PP Statistic	**1%Critical Value***
No constant	-0.427400	-2.5858
Constant and Trend	-2.218012	-4.0494
Constant-only	-2.013804	-3.4946

Unit root first difference testing:

	ADF Statistic	**1%Critical Value***
No constant	-4.548842	-2.5868
Constant and Trend	-4.729677	-4.0540
Constant-only	-4.522840	-3.4979
	PP Statistic	**1%Critical Value***
No constant	-6.351140	-2.5860
Constant and Trend	-6.400589	-4.0503
Constant-only	-6.319956	-3.4952

First difference stationary for All cases
*MacKinnon critical values for rejection of hypothesis of a unit root.

Table 2 HP-filtered Nonmetro Unemployment Rate Unit Root Tests for Nonstationarity

Unit root level testing:

	ADF Statistic	1%Critical Value*
No constant	-.793791	-2.5866
Constant and Trend	-2.21005	-4.0530
Constant-only	-.639844	-3.4972

	PP Statistic	1%Critical Value*
No constant	-.201116	-2.5858
Constant and Trend	-1.86729	-4.0494
Constant-only	-.797000	-3.4946

Unit root first difference testing:

	ADF Statistic	1%Critical Value*
No constant	-1.16907	-2.5868
Constant and Trend	-2.499539	-4.0540
Constant-only	-1.229069	-3.4979

	PP Statistic	1%Critical Value*
No constant	-1.582377	-2.5860
Constant and Trend	-1.688346	-4.0503
Constant-only	-1.577438	-3.4952

Unit root second difference testing:

	ADF Statistic	1%Critical Value*
No constant	-3.541395	-2.5868
Constant and Trend	-3.548646	-4.0540
Constant-only	-3.612122	-3.4979

	PP Statistic	1%Critical Value*
No constant	-1.965670	-2.5860
Constant and Trend	-2.050451	-4.0503
Constant-only	-2.016644	-3.4952

Second difference stationary for Constant case and
Constant-only case under ADF
*MacKinnon critical values for rejection of hypothesis of a unit root

Table 3 Cyclical Nonmetro Unemployment Rate Unit Root Tests for Nonstationarity

Unit root level testing:

	ADF Statistic	1%Critical Value*
No constant	-3.858305	-2.5866
Constant and Trend	-3.845710	-4.0530
Constant-only	-3.845752	-3.4972

	PP Statistic	1%Critical Value*
No constant	-3.313291	-2.5858
Constant and Trend	-3.292989	-4.0494
Constant-only	-3.303271	-3.4946

Unit root first difference testing:

	ADF Statistic	1% ritical Value*
No constant	-5.451445	-2.5868
Constant and Trend	-5.407213	-4.0540
Constant-only	-5.424648	-3.4979

	PP Statistic	1%Critical Value*
No constant	-6.863008	-2.5860
Constant and Trend	-6.789744	-4.0503
Constant-only	-6.827346	-3.4952

Stationary for No Constant and Constant-only cases
*MacKinnon critical values for rejection of hypothesis of a unit root.

Table 4 Metro Unemployment Rate Unit Root Tests for Nonstationarity

Unit root level testing:

	ADF Statistic	1%Critical Value*
No constant	-0.498519	-2.5866
Constant and Trend	-3.277836	-4.0530
Constant-only	-2.179791	-3.4972

	PP Statistic	1%Critical Value*
No constant	-0.509669	-2.5858
Constant and Trend	-2.605540	-4.0494
Constant-only	-2.022923	-3.4946

Unit root first difference testing:

	ADF Statistic	1%Critical Value*
No constant	-3.849239	-2.5868
Constant and Trend	-3.955981	-4.0540
Constant-only	-3.833749	-3.4979

	PP Statistic	1%Critical Value*
No constant	-4.597774	-2.5860
Constant and Trend	-4.640093	-4.0503
Constant-only	-4.577189	-3.4952

First difference stationary for All cases under PP
*MacKinnon critical values for rejection of hypothesis of a unit root.

Table 5 HP-filtered Metro Unemployment Rate Unit Root Tests for Nonstationarity

Unit root level testing:

	ADF Statistic	1%Critical Value*
No constant	-1.093540	-2.5866
Constant and Trend	-1.484666	-4.0530
Constant-only	1.025728	-3.4972

	PP Statistic	1%Critical Value*
No constant	-0.619140	-2.5858
Constant and Trend	-2.067657	-4.0494
Constant-only	0.124292	-3.4946

Unit root first difference testing:

	ADF Statistic	1%Critical Value*
No constant	-0.809142	-2.5868
Constant and Trend	-2.190287	-4.0540
Constant-only	-1.165311	-3.4979

	PP Statistic	1%Critical Value*
No constant	-1.646657	-2.5860
Constant and Trend	-2.030814	-4.0503
Constant-only	-1.782120	-3.4952

Unit root second difference testing:

	ADF Statistic	1%Critical Value*
No constant	-3.832126	-2.5868
Constant and Trend	-3.843400	-4.0540
Constant-only	-3.948533	-3.4979

	PP Statistic	1%Critical Value*
No constant	-1.946693	-2.5860
Constant and Trend	-2.030814	-4.0503
Constant-only	-2.002993	-3.4952

Second difference stationary for No Constant and Constant-only cases under ADF

*MacKinnon critical values for rejection of hypothesis of a unit root

Table 6 Cyclical Metro Unemployment Unit Roots Tests for Nonstationarity

Unit root level testing:

	ADF Statistic	1%Critical Value*
No constant	-3.450140	-2.5866
Constant and Trend	-3.459230	-4.0530
Constant-only	-3.443658	-3.4972

	PP Statistic	1%Critical Value*
No constant	-3.063264	-2.5858
Constant and Trend	-3.045233	-4.0494
Constant-only	-3.055118	-3.4946

Unit root first difference testing:

	ADF Statistic	1%Critical Value*
No constant	-4.696542	-2.5868
Constant and Trend	-4.669706	-4.0540
Constant-only	-4.674886	-3.4979

	PP Statistic	1%Critical Value*
No constant	-5.107754	-2.5860
Constant and Trend	-5.059693	-4.0503
Constant-only	-5.083481	-3.4952

Stationary for No Constant case
*MacKinnon critical values for rejection of hypothesis of a unit root

Notes for tables 1-6

Data 1973 first quarter to 1998 fourth quarter from Bureau of Labor Statistics and Economic Research Service

*MacKinnon critical values for rejection of null hypothesis of a unit root. If the test statistic exceeds the1% critical value then null hypothesis is rejected with 99 percent certainty. Both ADF and PP statistics accept nonstationarity in levels for all three versions of null hypothesis. So stationarity in levels is rejected, while first difference stationarity is accepted.

ADF Augmented Dickey Fuller Unit Root Test

PP Phillips-Perron Unit Root Test

No Constant Null Hypothesis = Random Walk

Constant and Constant Null Hypothesis = Random Walk plus time trend and constant.

Constant-only Null Hypothesis = Random Walk plus constant.

If the test statistic exceeds the critical value then the null hypothesis is rejected

PROBLEMS OF APPLYING CURRENT IMMIGRATION DATA TO UNITED STATES POPULATION PROJECTIONS

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Of the various sources of change in national populations that demographers must project in order to produce forecasts, international migration is undoubtedly the least suited to the application of demographic science. Births and deaths follow a demographically predictable relationship to the population being projected, which provides a clear application of simple demographic wisdom. While we may dispute the propensity of people at different ages to succumb to mortality, the importance of age and sex as factors predicting the number of deaths ensures that demographic science can contribute to its prediction. Similarly, the evolution of the population of women and men in the family-building ages contributes to our knowledge of the future number of births, although differing interpretations of the past may yield considerable uncertainty in the projection of the propensity of young women to bear children. For international migration, the factors determining its trend in most countries are sufficiently exogenous to the population and non-demographic in character that demographers are often confined to simplistic assumptions about its future course. In particular, we are especially reluctant to predict anything that depends heavily on the future course of national policy. To take U.S. Bureau of the Census population projections as an example, we have generally preferred to adopt a numerical constant estimate, based on the last few observed years of net migration, thereby assuming no change in international migration for a projection period of as much as 100 years. The recent increase in public debate regarding immigration policy, and the resulting focus on the immigration trend, has rendered such simplistic assumptions unsatisfactory.

In this paper, we focus on the interpretation of current administrative data on immigration. We will take as an example the experience of the United States in the decade now ending. Interpreting the current series is a critical aspect of the projection process, since even the most simplistic models of future international migration generally depend heavily on recent experience. We will posit further that an understanding of the legal characteristics of current international migration is a useful first step in the process of considering its future direction in the near to middle term.

Concepts and Data

At the outset, we need to note that the United States is not among those countries that maintain population registers identifying the nativity or citizenship of its inhabitants. Such registers have the advantage of identifying relatively clearly the residency status of foreign-born persons, as well as their admission to the country. Because, the U.S. does not have such a data entity, international migration must be estimated from data on administrative events relating directly to the flow of individuals in and out of the country, specifically in and out of U.S. residency. Superficially, this appears unproblematic, since it is precisely the movement of people in and out of the country that represents the non-natural component of population change at the national level that we seek to estimate. However, the events measured by administrative data do not necessarily coincide with the events that we seek to measure.

In the match of data to the population universe being estimated, it is necessary to consider three concepts of migration to the country, 1) admission to legal permanent residency in the United States, 2) physical entry into the United States, and 3) acquisition of U.S. residency as defined by our census, determined by where an individual lives most of the time. The third concept is the one that we seek to quantify, since the decennial U.S. census forms the basis for population estimates and projections. Were we to employ a data source that measured all movement across the national frontier, we would be concerned with the distinction between 2) and 3), since we would be measuring physical entry. Such a data base does not exist, since there is no mechanism for complete measurement of departures. Consequently, we rely principally (but not entirely) on the admission to legal permanent residence, or legal immigration, in U.S. administrative parlance. As long as the data source under consideration relates to legal immigrants, the distinction between residency concepts 1) and 3) above is of principal concern.

The principal immigration data source is a file produced by the U.S. Immigration and Naturalization Service (INS) in the U.S. Department of Justice, that provides individual-level information on persons who become legal permanent residents of the United States. In official

statistics of the INS and other agencies, the term "immigration" is used to refer to the acquisition of legal permanent residence, rather than physical entry into the country. The information on the file includes (among other things) month and year of admission to legal permanent residency, age, sex, and country of birth. Most importantly, it includes a class-of-admission code that identifies whether an individual physically arrived at the time of immigration or whether the person was already in the United States prior to immigration. The code also identifies the legal provision under which the immigration occurred. The availability of the class of admission code is critical, as it allows us to tabulate the legal basis for immigration, which is not only critical to our understanding of current population change, but also provides some basis for projecting the future dynamics of immigration.

Trends Arising from Changes in the Law

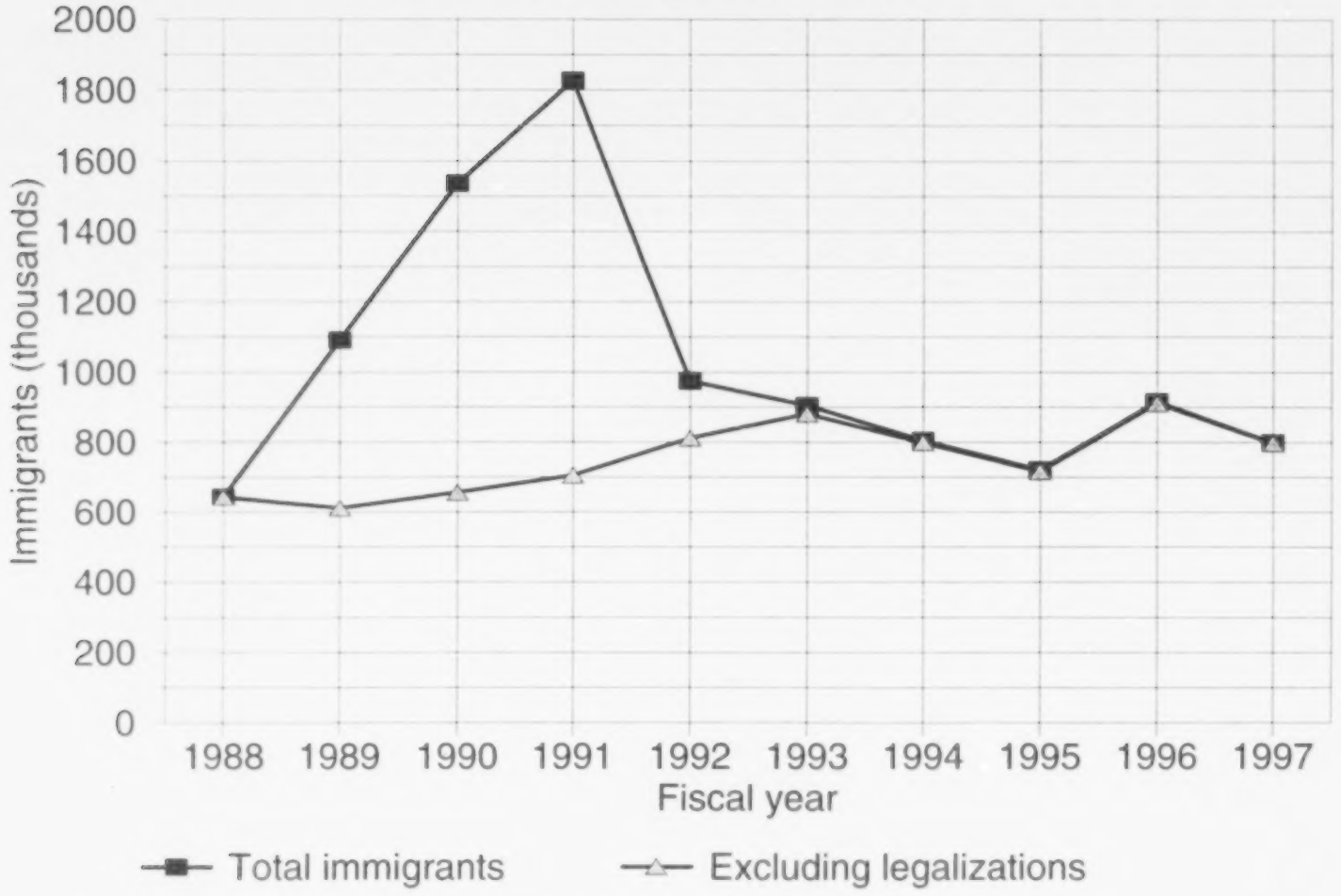
An especially dramatic example of how legal immigration is misleading as a measure of change of residence is illustrated by Figure 1. In this chart, we have plotted two immigration series. The first is the trend from 1988 to 1997, by fiscal year, in the total number of immigrants to the United States. This series shows a dramatic rise from 643,000 to 1,827,000 from 1988 to 1991, followed by an equally dramatic fall to 974,000 by 1992, and a fluctuating downward trend through 1997. This "spike" in U.S. immigration was a result of a specific policy event that occurred in the United States in 1987 to 1988, namely the enactment of a law, the Immigration Reform and Control Act of 1986, that legalized the residency of roughly 3.5 million people who had previously been residing illegally. The provision took the form of an amnesty that was available for about one year. Under its provisions, all legalized persons had to be residing in the United States in 1987, and had to meet one of two criteria, one of which (met by roughly half) was continuous residency since 1982. Were these criteria met, it was possible to become a legal permanent resident without meeting the normal requirements for immigration, which explains the enormous rise in immigration ending in 1991. Clearly, these immigrants would not have arrived at the time they became legal residents, or since the 1990 census. The observed spike should not be included in 1990-based estimates of population, and is of no relevance to a projection of future resident arrivals. The second line on the graph shows the trend with these persons excluded, exhibiting a gradual increase that tends to be masked by fluctuations late in the decade. While the need to exclude immigrants already in the country in the base year and admitted through a past legal event appears obvious, this immigration class of legalized aliens nevertheless is included in most published accounts of immigration to the United States, because they are indeed immigrants in the legal sense.

Delayed Acquisition of Permanent Residence

A less dramatic but more pervasive problem arises when people enter the country either illegally or with a visa for a legal temporary stay, and subsequently meet legal qualifications for immigration. While the INS maintains data on the issuance of nonimmigrant visas by visa type (including tourist and other temporary visa categories), it is normally not possible to distinguish between temporary admissions that depart without establishing residence, those that establish residence but do not legally immigrate, and those that subsequently immigrate. As a result, the practice has generally been to assume that the number of temporary entrants already residing in the U.S. that immigrate each year is equal to the number that enter the U.S. and will immigrate in a subsequent year. If the flow of such persons is reasonably constant from one year to the next, and the duration of residence from arrival to legal immigration is reasonably stable, the assumption is sound.

However, two major developments in the past 20 years have rendered this assumption unacceptable in certain situations. First, in 1975 and 1980, there were dramatic peaks in the movement of refugees to the United States. Both of these years saw waves of refugees from Southeast Asia, principally Vietnam, resulting from the end of the Vietnam War and the subsequent absorption of "boat people" from refugee camps in Thailand. In 1980, moreover, the United States received a flotilla of over 100,000 persons from Cuba. Both categories of persons were ultimately eligible for legal immigration to the United States; both would also be considered U.S. residents at time of arrival, since the intent of most refugees was to remain in the United States. In the case of the Southeast Asian refugees, the elapsed time from arrival to the acquisition of legal permanent residence was highly variable, to the point that even in the early 1990s, a substantial number of these refugees were still becoming immigrants, although most had resided in the United States for many years. Waves of entrants to the U.S. from the Soviet Union during the 1980s, and from the former Yugoslavia in the last few years, while less dramatic, have also served to upset the validity of immigration as a proxy for residential migration to the U.S. in a year-to-year trend. Fortunately, an alternative data series provided by the Office of Refugee Resettlement in the Department of Health and Human Services has allowed us to measure refugees directly by time of arrival, while the class of admission code in the

Figure 1
Published Immigration Series



Source: Immigration and Naturalization Service, Statistical Yearbook

INS immigrant data has allowed the parallel exclusion from the immigrant data series to avoid double-counting.

A second major challenge to our evaluation of the trend in "delayed immigration" occurred in the last few years, beginning with fiscal year 1995. A temporary change in the law regarding the immigration procedure for illegal residents had a disturbing effect on the interpretation of current immigration data. People who met the qualifications for legal immigrant status while residing illegally in the United States had been required to return to the country of origin and reenter legally by immigrating through the Department of State, normally by applying to a U.S. embassy. Under the new provision, first implemented in fiscal year 1995, such a person could apply for legal immigration to the INS without leaving the U.S., upon payment of a fine. The relative attractiveness of this alternative resulted in an enormous rush of immigration applications to the INS from within the United States, which the agency was unequipped to fully process, and a major backlog of pending immigrant applications developed (Immigration and Naturalization Service, 1997, p. 13). As a result, the number of adjustments to legal permanent residence in two years, 1995 and 1997, grossly understated the number that would normally have adjusted.

Our approach to this problem was to base estimates of would-be adjustments to legal permanent residence on the number of received applications, rather than on the number of actual immigrants. Allowance was made for applications that would not result in immigration, based on data from years where applications and immigrants were in their normal balance. We also constrained the number of imputed immigrants to comply with numerical limitations by class of admission. The latter procedure was somewhat tenuous, as no actual data on the admission class of applications (as opposed to immigration events) were available. We emphasize that the object of this procedure, an estimate of the number of adjustees to permanent resident status, is itself an indirect estimate of the number of changes of residence into the U.S. that will later result in a legal immigration. Hence, there are two levels of uncertainty superimposed on this process.

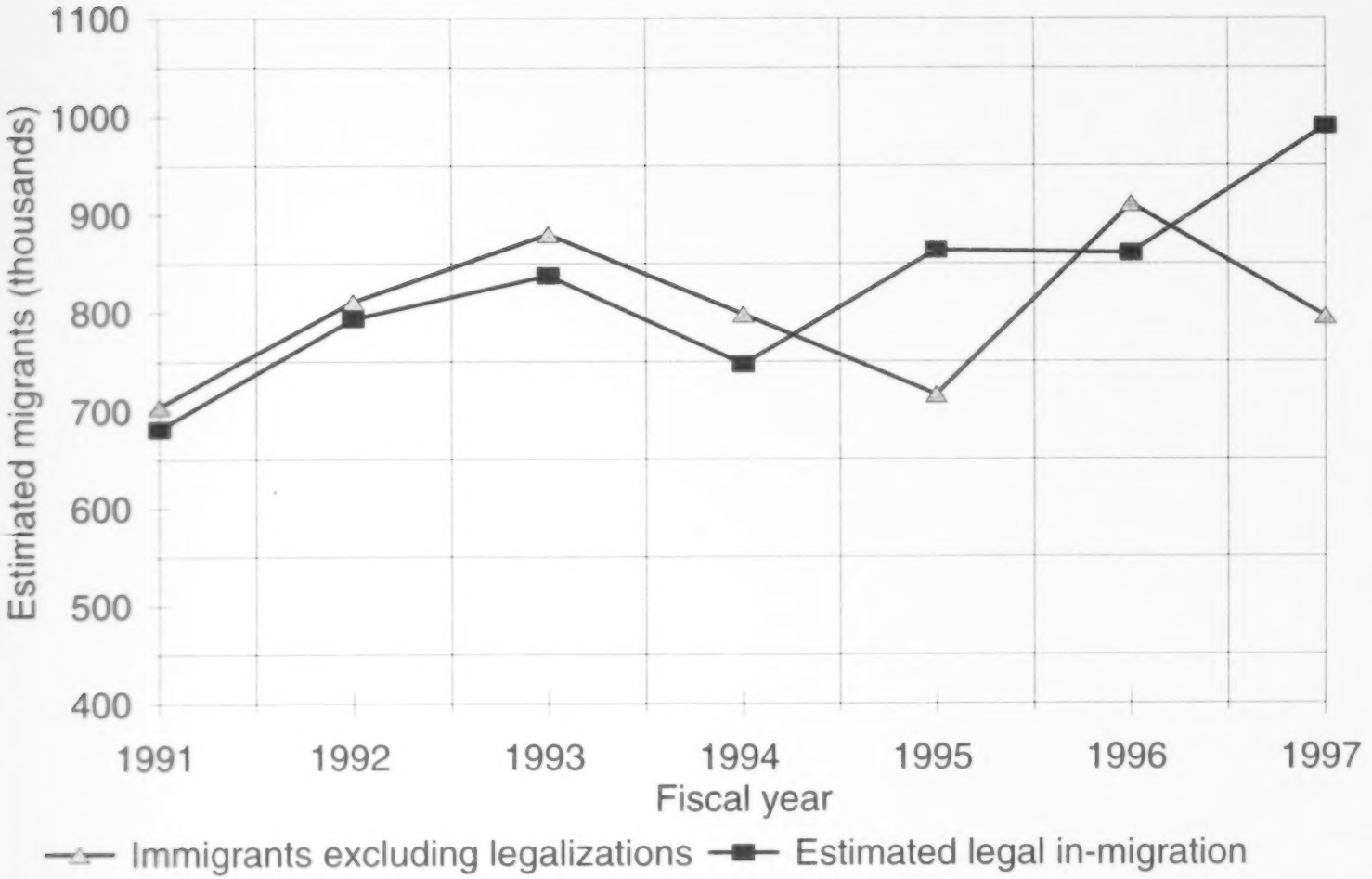
The result of our adjustment for these two data problems is shown in Figure 2. The line entitled "immigrants excluding legalizations" matches the second line in Figure 1, although on a larger scale, and is restricted to the period since 1991. The second line, "estimated legal in-migration", represents the result of our substitution of independent data on refugee arrivals as well as our attempt to correct for the post-1995 backlog. The former is reflected in the relatively small reduction in the in-migration estimates for 1991 to 1994, because the number of erstwhile refugees adjusting to legal immigrant status overstated the number of new refugees entering the country. The correction for the application backlog beginning in 1995 changes the migration trend from a possible increase masked by fluctuation to a relatively steady, and somewhat sharper increase through 1997. Clearly, this distinction would be of importance to any long-term projection that would hold international migration constant at levels observed in the last half of the current decade. Such a projection without the adjustment of the current series would most likely be too low. It would be of even greater importance to any assumption that would extrapolate change--even in the near to middle term--through the 1990s, since the trajectory of the trend apparent in the actual immigration data is biased downward if our estimates of the adjustment are correct.

Numerical Limitations and the Legal Basis for Emigration

While we have considered the effect of some legal developments as determinants of the current trend in legal migrations to the United States, a consideration of the different legal bases for migration that exist within that trend is essential to the consideration of its near-term future. U.S. immigration law is quite complex, and is to a large extent the result of successive, incremental changes that have been made to existing laws. However, a relatively major overhaul of immigration policy occurred with the passage of the Immigration Act of 1990, which sought to place an overall cap on immigration, but allowed the cap to be compromised by higher-than-expected demand for the reunification of families of U.S. citizens. The new law identifies the following major classes of immigrant admission to the U.S., accounting for most immigrants in the 1990's.

> 1) Immediate relatives of U.S. citizens, principally spouses, dependent children, and parents. There is no numerical limit imposed on this category.
>
> 2) Immediate relatives (spouses and children) of legal permanent resident non-citizens, as well as siblings, non-minor children of U.S. citizens. The numerical limit is determined each year as 480,000 minus the number of admissions to category 1) in the previous fiscal year, except that the

Figure 2
Correction for Arrival and Processing



limit may never be less than 226,000. From 1992 to 1994, a special category for dependents of legalized aliens was provided, with a separate annual limit of 55,000.

3) Persons having various marketable skills, making them uniquely eligible for certain types of employment. The numerical limit is 140,000 in a fiscal year.

4) Persons selected under a "diversity lottery", a random choice of persons submitting applications from countries that were underrepresented among immigrants of the preceding five years. The numerical limit is 55,000 in a fiscal year.

5) Refugees and asylees. This category is not numerically limited, but its magnitude is dependent on various legal provisions that may change in response to world events.

The limitations on these categories are intended to ensure that the first four categories should sum to a maximum of 675,000 per year, provided that the unlimited first category (immediate relatives of U.S. citizens) does not exceed 254,000. To the extent that this category exceeds 254,000, the overall target level of 675,000 may be exceeded as well (Immigration and Naturalization Service, 1999, p. 7).

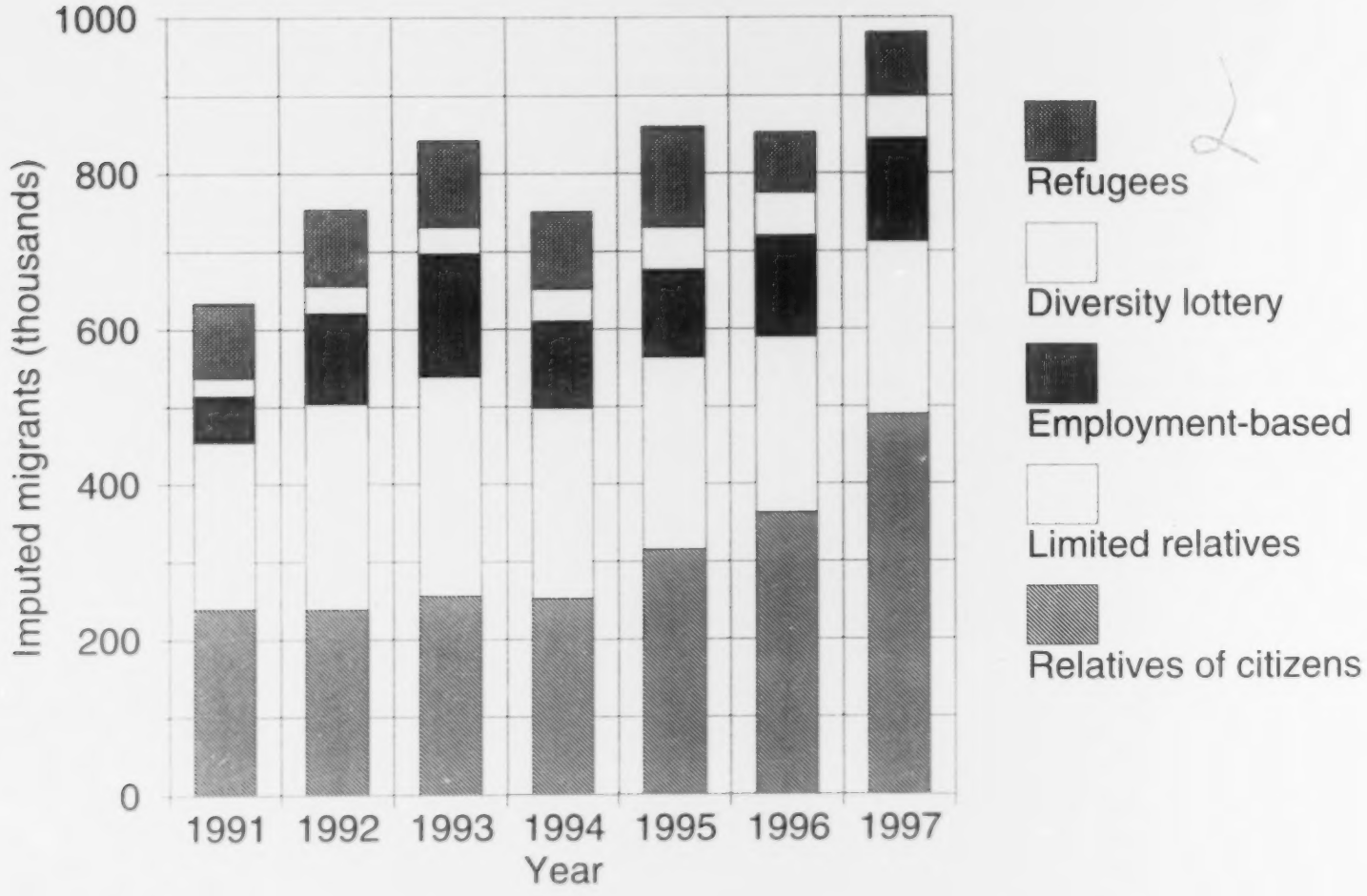
The current decade has seen a sharp rise in the immigration of immediate relatives of U.S. citizens, as shown in Figure 3--far above the target 254,000. This chart is based on the distribution of estimated in-migrants, not actual legal immigrants, and thus reflects the adaptations discussed previously in this paper. Also apparent, although less obvious, is a gradual decline in the number of refugees. Relatives of resident aliens ("limited relatives", in the chart) have maintained a relatively constant level in recent years; in fact, after adapting the number of citizen relatives for the effects of the post-1995 application backlog, the limitation for relatives of non-citizens maintains a constant level of 226,000 per year. The special provision for dependents of legalized aliens in the early 1990's was utilized to near capacity. Employment-based immigration has fallen 10,000 to 20,000 short of its limit in the last few years, according to these estimates. The diversity lottery has reached its cap of 55,000 consistently since 1995.

If we were to project legal migration to the U.S. from abroad through the near term, based on current trends, the most likely source of change would be a continued increase in the number of persons admitted as immediate relatives of citizens. However, we must recall once again the effects of one-time legal provisions. While the Immigration Reform and Control Act resulted in the legalization of a large number of undocumented aliens already residing in the U.S. in the 1980s, it also provided for their accession to legal permanent residence, and (indirectly) their later accession to U.S. citizenship. Consequently, their spouses and children inherit the legal basis for immigration to the United States--initially within a quota, but ultimately without limitation. This largely explains the rise in this unlimited class of immigration to the United States. This reasoning is further supported, as we observe that both the legalization immigrants early in the decade and the family reunification immigrants late in the decade are predominantly of Mexican birth. While it is quite likely that the near-term future will see further increases in the reunification of families with new citizens, it would be imprudent to project a continued sharp upward trend in this source of migration for many years into the future. The reason for this caution is simply that the number of legalized immigrants is not increasing, so that this source of legitimation for new immigration must attenuate over time. We note, parenthetically, that there is some limited potential for the extension of this trend through the extension of families. For example, if adult siblings of a U.S. citizen are admitted within numerical limitations, their children can later be admitted without limitation. It is unlikely that this will have a major long-term effect, however. Finally, the flow could be renewed in the event of any additional legislation to legalize undocumented residents. Such legislation appears unlikely in the near future.

Components of Migration Without Legal Basis

Three components of international migration to the United States have no basis in law, so that the analysis of legal factors underlying migration events is of little or no use to projections. The first is the net increase of the population arising from undocumented migration, excluding those who ultimately qualify for legal immigration. In current Census Bureau estimates of the U.S. population, we assume this to be 225,000 per year. Estimates of the Immigration and Naturalization Service indicate a somewhat higher level of 281,000 through 1992 and 275,000 thereafter (Immigration and Naturalization Service, 1997, p. 198). However, INS estimates do not purport to exclude those who would be

Figure 3
Legal Components of Legal In-Migration



missed by a census, whereas our estimates of 225,000 purport to represent only those who would be enumerated.

The emigration of legal residents (citizens and non-citizens) is unrestricted, and (since 1957) unregistered. The annual magnitude of the foreign-born component of this flow was estimated by Ahmed and Robinson (U.S. Bureau of the Census) to be about 195,000 per year in the 1980s (Ahmed and Robinson, 1997). This estimate, and some of the country-specific data underlying it, were used to develop a schedule of rates of emigration used to project emigration through the 1990s, and ultimately into the future. Most emigration from the United States occurs among foreign-born persons. Ideally, one could foresee a rather sophisticated model in which emigration rates are applied to populations defined not only by nativity, but by duration of residence in the United States, since both are likely to be decisive factors in the decision to emigrate. However, no such model has yet been developed for the United States, and it is unlikely that current data would support such a model.

Finally, a third class of "international" migration to the U.S. escapes direct measurement because it is composed almost entirely of U.S. citizens who require no documentation for their moves. This is the balance of migration between the U.S. and Puerto Rico, as well as U.S. possessions and trust territories overseas. It is treated as international, because it involves the movement of people across the frontier of the territory for which we produce estimates and projections, even though it does not involve many non-citizens. We assume the net flow of migration between these areas and the U.S. to be nil, except for the case of Puerto Rico, where we assume a balance of 12,000 per year migrating from Puerto Rico to the U.S., based on an imputation done for the 1980s.

Conclusion: the Projection of International Migration

This work has considered a number of structural issues that can be measured from current data on immigration, and are determined by the laws governing immigration. We have shown that "raw" immigration numbers can be misleading as a proxy for actual migration of non-citizens from abroad. We have also shown that the data themselves can possess the basis for estimating an adjustment. Such consideration is worthwhile with respect to projections, for two reasons.

> 1) To the extent that we can correct bias in the current estimation of population change, we can provide an improved current estimate of population on which to base future projections.
>
> 2) To the extent that the correction of this bias affects the trajectory of an international migration series, the correction also forms the basis for more defensible projections of international migration as a component of population change to future dates.

A second issue that we have emphasized is that an examination of the legal basis for current immigration provides a clue to its future projection--especially in the near term. If a migration flow is based largely on the immigration of persons under legal provisions with numerical limitations, then only a change in the law can affect this class of migration. On the other hand, if a segment of legal immigration occurs without numerical limitation, it is necessary to consider the factors that underlie it, in determining how it will change in the future.

For the purpose of producing longer term projections of international migration (assuming "longer" might be a period of time in excess of 15 to 20 years into the future), the effects of current policies should attenuate, as the likelihood of their revision increases. In the context of a political system in which decisions regarding immigration policy are made by elected officials, there is understandable reluctance on the part of demographers to forecast future international migration, especially to forecast it dynamically. It is simply too much a function of political issues that do not lend themselves to demographic forecasting. Yet, the assumption of "constant present" tends to be less than satisfactory, simply because it is unclear what should be held constant. Should it be the number of immigrants, a schedule of rates based on the subject population, or rates based on sending populations with some weighting scheme? It is likely that the most prudent long-term projection of international migration is one that considers the changing demographic structure of the population, as it affects dependency and the supply and demand for labor, as well as the role of differential economic development as an impetus for changes in the migration balance among different countries of the world.

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CONTINGENT FORECASTING OF THE PROPORTION WITH SMALL INCOMES IN A VULNERABLE NONMETRO POPULATION

John Angle, Economic Research Service

Introduction

This paper begins with noticing a feature of the time-series of the proportion of nonmetro small incomes by level of education: the greater dispersion of the time-series of the less well educated around their mean proportion. See Figure 1. 'Nonmetro' indicates residence in a county not designated as 'metro' by the Office of Management and Budget. Metropolitan Statistical Areas include core counties containing a city of 50,000 or more people or have an urbanized area of 50,000 or more and total area population of at least 100,000. Additional contiguous counties are included in the MSA if they are economically integrated with the core county or counties. The nonmetro population has lower levels of educational attainment and a larger proportion of small incomes than the metro population. The Economic Research Service is tasked with statistical reporting on the nonmetro population, particularly its vulnerable segments such as the nonmetro population with at most an elementary school education and a small income.

You might think that a noisy statistic such as the proportion of small incomes among nonmetro people with at most an elementary school education would be hard to forecast, but it can be reliably forecasted on a contingent basis, that is, given a forecast of another statistic, their median income. If, for example, you have an accurate forecast of how far the median income of nonmetro people with at most an elementary school education will fall in the next recession, this paper's method produces almost as good a forecast of the proportion of that population with small incomes. This paper shows that the proportion of small incomes among nonmetro people with little education rides a roller-coaster over the business cycle (growing more when the national income median falls, decreasing more when the national income median rises) as a consequence of the shape of their income distribution. The shape of their distribution is related to their median. Consequently, the movement of people's incomes by any suitably chosen maximum small income is related to their median. The nonmetro population with little education and income is a vulnerable population in a recession. Welfare benefit programs have been reduced during the recent business expansion, i.e., when they are least needed. There is reason to be concerned about how big the nonmetro low education, low income population may become in the next recession since many may need welfare benefits. This paper allows forecasts of the median income of nonmetro people with little education to be converted into a good contingent forecast of the proportion of that population with small incomes, however defined, i.e., if the forecast of the future median becomes true, the contingent forecast of the proportion of small incomes will be accurate.

The Greater Dispersion of the Proportion of Small Incomes among Incomes of Nonmetro People with Less Education

The starting point of this paper is the time-series of Figure 1, the proportion of small incomes of nonmetro people in the U.S. age 25 to 65 from 1963 through 1995 by level of education. 'Income' here means personal annual money income, using the U.S. Bureau of the Census definition. Figure 1 is based on the March Current Population Survey from March 1964 through March 1996. The March Current Population Survey (CPS) is a household survey with a large sample drawn and interviewed by Bureau interviewers. It collects data on annual personal money income in the previous calendar year. The March CPS data were obtained from the Unicon Research inc., a data reseller (Unicon, 1997).

Small incomes are defined here as incomes from $1 to $8,000 in terms of 1989 dollars. The rationale for $8,000 is that it is half of $16,000 (in terms of 1989 dollars), which is just below the low point of the median of personal annual income in terms of constant 1989 dollars of the whole U.S. population 25 to 65 years with at least $1 in personal annual income in the early 1980s. See Figure 2. The half-median of personal income is sometimes used as an estimate of the upper threshold of poverty. Current dollar values have been converted to 1989 dollars using the consumer expenditure price deflators of the Council of Economic Advisers (1998). This paper's conclusions also hold for a maximum small income of $4,000 or $12,000 in 1989 dollars.

The perhaps most salient aspect of Figure 1 is the fact that there is a larger proportion of people with small incomes among the less educated. The second most salient feature of Figure 1 is that the five time-series of the proportion of small incomes by education move up and down to some degree together because they are all similarly correlated with the national median of personal income of people age 25 to 65 with at least $1 of income from 1963 through 1995. See Figure 2. The recessions indicated in Figures 1 and 2 are defined by

the National Bureau of Economic Research (1998). The correlations between the proportion of small incomes by level of education and the national median from 1963 through 1995 are:

highest level of education	correlation between proportion of nonmetro small incomes and national median	standard errors of 100 bootstrap resamplings
at most elementary school	-.52507	.10437
some high school	-.35963	.12761
high school graduate	-.57789	.10203
some college	-.53213	.10007
at least a college graduate	-.60334	.09810

The correlations are all negative because the proportion of small incomes tends to move inversely with the national median regardless of education level.

There is a third feature of Figure 1, the greater dispersion of the proportion of small incomes of the less educated around their mean. The time-series of the most educated group, those who are at least college graduates, is not much improved by the prosperity of the late 1960s, is almost level during the early 1970s, moves up less than the other curves during the increasing economic distress of the late 1970s, and gradually returns to its previous level after. By contrast the time-series of the least educated group plunges in the late 1960s, turns and heads up sharply in the late 1970s and early 1980s, also just following the recession of the early 1990s. The time-series of intermediate levels of education behave intermediately.

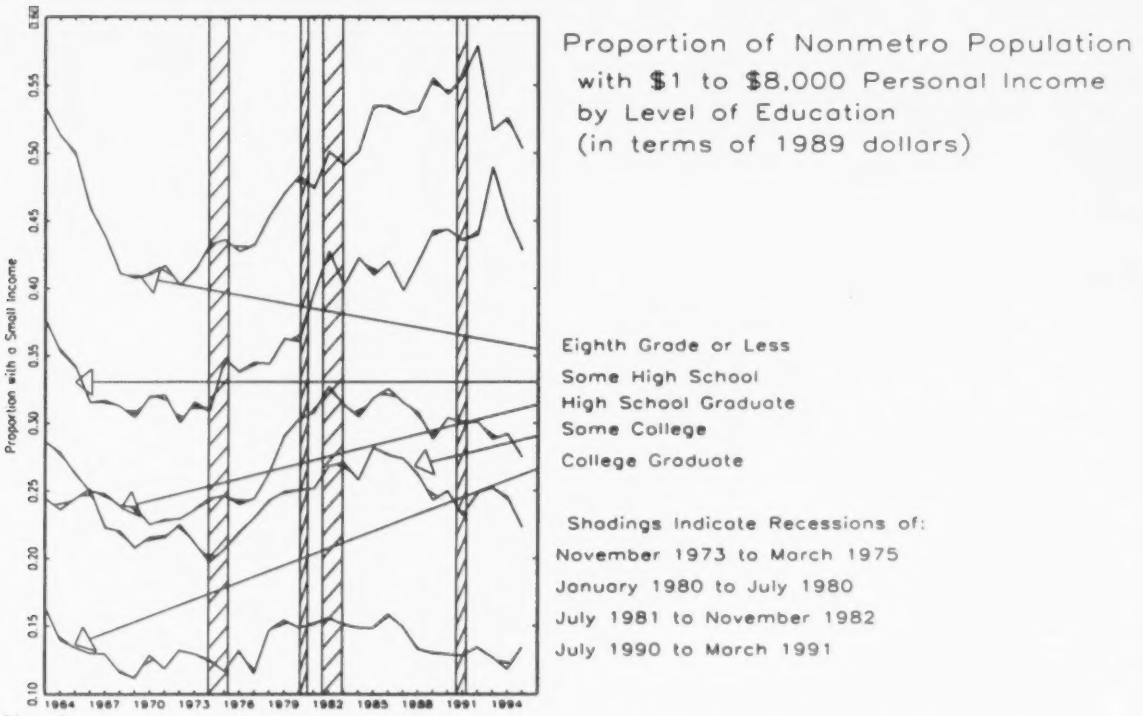

Figure 1

Note: Nonmetro population 25 to 65 years with at least $1 in personal income. Each time series is ratio, (number of people at education level i with a small income) / (number of people at level of education i), from 1963 through 1995.

Source: March Current Population Survey

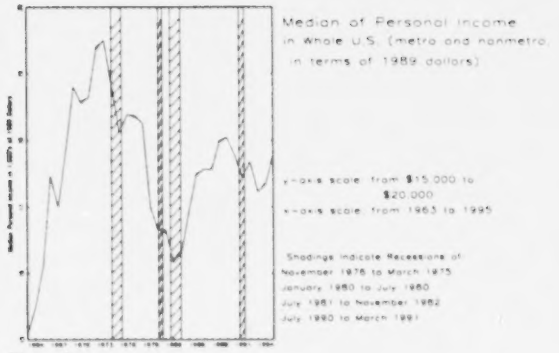
Median of Personal Income
in Whole U.S. (metro and nonmetro,
in terms of 1989 dollars)
y-axis scale: from $15,000 to
$20,000
x-axis scale: from 1965 to 1995
Shadings indicate Recessions of:
November 1973 to March 1975
January 1980 to July 1980
July 1981 to November 1982
July 1990 to March 1991

Figure 2
Note: People age 25 to 65 (metro and nonmetro) with at least $1 in personal income.
Source: March Current Population Survey

The dispersion of each of the five time-series can be measured by its estimated standard deviation around its mean:

highest level of education	correlation between proportion of small incomes and national median	standard errors of 100 bootstrap resamplings
at most an elementary school education	.05221	.00385
some high school	.05367	.00454
high school graduate	.03251	.00213
some college	.02201	.00194
at least college graduate	.01394	.00126

With one exception, the standard deviations scale inversely with level of education. The standard deviation of the least educated group is about four times that of the most educated group.

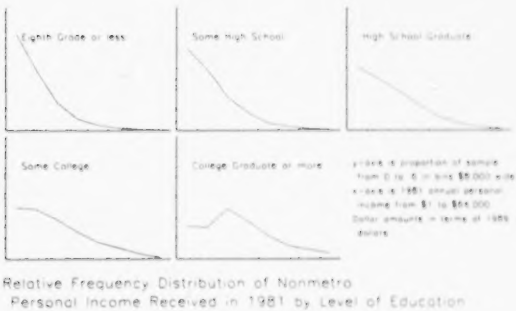
Eighth Grade or less
Some High School
High School Graduate
Some College
College Graduate or more
Relative Frequency Distribution of Nonmetro
Personal Income Received in 1981 by Level of Education

Figure 3

A Speculation about the Greater Dispersion of the Time-Series of the Proportion of Small Incomes among the Less Educated

The shape of income distributions in 1981 varied by level of education. See Figure 3. The distribution of the those with at most an elementary school education is almost convex down, while the distribution of the most educated group is concave-convex down, less right skewed, and more symmetric. The distributions of intermediate education levels are intermediately shaped. They form a scale in terms of shape from one extreme to the other but descriptors such as more "convex down" or more "concave-convex down" are inadequate to describe the gradations from one shape to the next.

In the more convex down shaped distribution, that of the people with at most an elementary school education, there is a larger proportion of incomes close to the left limit of the distribution, i.e., they are either in the $1 to $8,000 (in 1989 dollars) range of incomes or just above it. The proportion of small incomes in the distributions of more educated groups is smaller. The variation in this proportion over levels of education is a consequence of the relationship between education and the whole shape of income distributions. If the distributions of Figure 3 define the continuum of shapes that distributions of income conditioned on education can assume, then random change in the shape of the more convex down income distribution, with more of its area over small incomes, will move more of this area past an arbitrarily chosen small income than will random change in the shape of less convex down income distributions. One might speculate that it is the more convex down shape of the income distributions of the less well educated that accounts for the greater dispersion of their proportion of small incomes.

There are three conditions that need to be established for this speculation to be true. First, the range of distribution shapes of Figure 3 has to be a stable

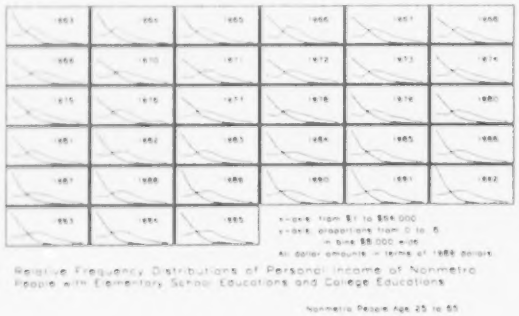
Relative Frequency Distributions of Personal Income of Nonmetro
People with Elementary School Educations and College Educations
Nonmetro People Age 25 to 65

Figure 4

phenomenon, something that is enduring, i.e., generally characteristic of the conditional distribution, income conditioned on education. Secondly, the continuum of shapes of Figure 3 has to be measurable, preferably by a measure that projects shape into a single numeric scale. This model of shape should be able to measure the full range of observed distribution shapes and intermediate shapes. Thirdly, it is has to be shown that in terms of this model, year-to-year changes in shape that are equal for all education groups imply that the proportion of small incomes in distributions shaped like that of the least educated group (convex down) will change more than that proportion in less convex down income distributions.

Condition 1: The Stability of the Continuum of Shapes

Figure 4 shows that the income distributions with the most extreme shapes, the convex down distribution of people with at most an elementary school education and the mixed concave-convex down of those who are at least college graduates, while varying somewhat from 1963 through 1995, maintained their shapes. The same can be said for intermediate levels of education, but there is a more precise way of establishing the stability of the shapes of income distributions by level of education. When Condition #2 is fulfilled Condition #1 can be met more precisely.

Condition 2: A Model of Income Distribution Shape That Projects Shape into a Numeric Scale

The two parameter gamma family of probability density functions (pdf) provides a description of the shapes of the income distributions of Figure 3. See Figure 5. The gamma pdf has a continuum of shapes

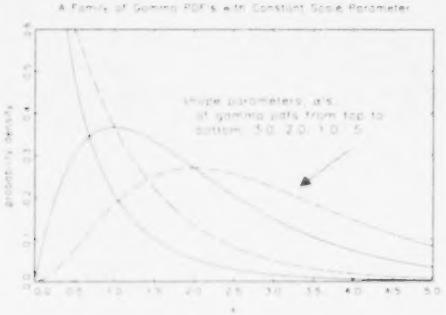

Figure 5

running from convex down to a less right skewed concave-convex down shape. These shapes are controlled by the shape parameter, alpha. The other parameter, the scale parameter, either compresses the shape of the distribution to the left or stretches it to the right. The gamma pdf has been used for a century to model income distributions. The gamma pdf is defined by:

$$f(x) \equiv \frac{\lambda^{\alpha}}{\Gamma(\alpha)} x^{\alpha-1} e^{-\lambda x}$$

where:

$$x > 0$$

$$\alpha > 0$$

$$\lambda > 0$$

Figure 5 displays the shapes that the gamma pdf takes as its shape parameter, α, is varied while its scale parameter, λ, is held constant. Since all dollar values in March CPS data on annual personal incomes are measured in terms of a single scale, 1989 dollars, the scale parameter of a gamma pdf fitted to the 165 (= 33 years x 5 education levels) partial distributions in these data should be constrained to a single value.

To show that the gamma pdf so constrained is a good descriptor of all the shapes that the income distribution conditioned on level of education can assume, the gamma pdf is fitted to all 165 distributions simultaneously. The fitting is done via OLS applied to the linearized gamma pdf, that is, the natural logarithm of the gamma pdf, a transformation which makes it a linear combination of x and ln(x). Here 'x' is mean annual personal income in a frequency bin. The frequency bins are each $8,000 wide. There are eight of them per distribution fitted for 1,320 (= 8 frequency bins x 165 distributions) relative frequencies to be fitted. One scale parameter is estimated. Five shape parameters of the education groups are estimated as the sum of the coefficient of the ln(x) term and the coefficient of the appropriate interaction term between ln(x) and the set of four binary variables for education level. There are 37 other parameters estimated which are not directly used to estimate the five shape parameters (1 global intercept, 32 intercepts for the 33 years, and 4 intercepts for the five education groups). The measure of fit is squared correlation between the observed relative frequencies and expected relative frequencies. The squared correlation is 0.93687, a tight fit, considering the 165 distributions fit and the long length of time over which they were observed. The income distributions of five education groups over thirty-three years have been fitted by a gamma pdf with one scale parameter and one shape parameter for each of the five education groups. These parameters are not allowed to change over time. Since this model fits, it means 1) that the gamma pdf model with the constrained scale parameter is a good model of the 165 distributions, fitting with parsimony, and 2) that there has been little change in distribution shape by level of education over

this long period, i.e., the shape of the income distribution of each education level is an enduring phenomenon. This fit shows that the shape parameter of the gamma is a useful numerical scale of the shape of income distributions conditioned on education.

Condition 3: A Way of Measuring Small Changes in Distribution Shape Equal for Each Education Group

The gamma pdf fit of Condition #2 shows that the hypothesis of no change in the shapes of distributions of income by level of education does well. This gamma pdf fit also demonstrates in a more precise way than Figure 4 that the shapes of income distributions by level of education in the U.S. have not changed much from 1963 through 1995, i.e., Condition #1 is satisfied. But the hypothesis of this paper is that a small change of shape in a more convex down down income distribution moves more incomes past $8,000 than the same small change in a distribution with a less convex down shape. So another fit of the gamma pdf to the 165 distributions of income by level of education (5) and year (33) needs to be undertaken, this time allowing for year to year change. This year to year change must be in some sense an equal perturbation of all five education groups. This requirement is imposed stipulating that the time-varying component of the shape parameter of each constrained gamma pdf fitted to an education group's income distribution in a particular year is equal to the time-varying component of the shape parameter of the gamma pdf fitted to the income distribution of the other education groups in that year. Instead of fitting a gamma pdf with α_i to the ith education level's income distribution in all thirty-three years, a gamma pdf with shape parameter ($\alpha_i + \alpha_t$) is fitted to the income distribution of the ith education group in year t.

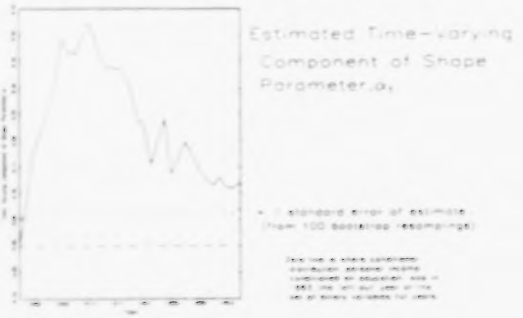

Figure 6

These annual components are estimated as the coefficients of the interaction of the 32 binary variables for the 33 years with ln(x), the natural logarithm of income, additional terms in a model otherwise identical to the one just fitted via the linearization of the gamma pdf. The estimated coefficients of each year are given in Figure 6. The "left out" (or base) category of this set of binaries is the first year, 1963. It is set at zero. The year effect coefficients correlate .7290 with the national median of income (Figure 2). The estimated shape parameters of each level of education, net of year-to-year variation, are:

highest level of education	estimated shape parameter net of year effects	standard error of 100 bootstrap resamplings of regression disturbance terms
at most elementary school	.84870	.04966
some high school	1.15272	.05048
high school graduate	1.49675	.04678
some college	1.73593	.05250
college graduate	2.30466	.05109

The single estimated scale parameter is 0.000099768. The squared correlation between the 1,320 observed and estimated relative frequencies under this model is 0.94633, a better fit, purchased at the price of 32 degrees of freedom. Clearly the change of shape of income distributions in this period has been small, so small that allowing an annual adjustment to shape does not improve the fit much. The F-test for the increment in the r-square of the linearized gamma with the addition of the 32 interaction terms is statistically significant.

The Conclusion of Condition #3 and the Speculation

The gamma pdf provides a continuum of distribution shapes that is clearly relevant to the conditional distribution, income conditioned on education. The gamma pdf with scale parameter constrained to a single common value, makes fitting income distributions of various shapes nearly a sole function of the shape parameter of the gamma pdf, essentially reducing distribution shape to a single numeric scale. Now all that remains to be done is to demonstrate that change in the area in the left tail of a gamma pdf, defined analogously to the left tail of an empirical income distribution, is more

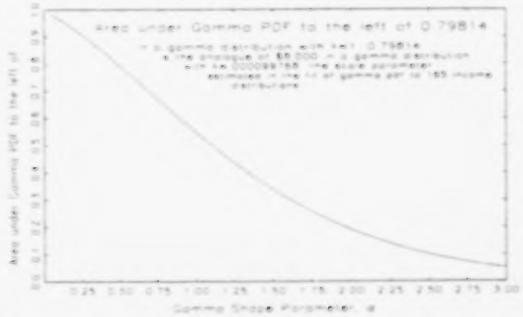

Figure 7

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closely related to change in the shape parameter of the gamma pdf when the shape parameter is smaller than when it is larger. This issue is the question of how steep is the slope of the area of the left tail of a gamma pdf as a function of its shape parameter over small and large shape parameters

Figure 7 displays the curvilinear relationship between the left tail of the gamma pdf as a function of its shape parameter. The left tail of the gamma pdf graphed in Figure 7 is defined analogously to the left tail of empirical income distributions being defined by incomes from $1 to $8,000 in 1989 dollars. The single gamma scale parameter estimated from the 165 fits to the 165 partial distributions of the conditional distribution of income conditioned on education is .000099768. The analogue of $8,000 in a gamma pdf with scale parameter 1 is .000099768 x 8,000, or .79514. The left tail areas of Figure 7 are estimated from gamma pdfs with scale parameters all equal to 1.0. These estimates are derived by numerical integration of the gamma pdf. Since the gamma pdf cannot be evaluated at 0.0, the integrations are performed not from 0 to a particular shape parameter but from the shape parameter to a very large number and then subtracted from 1.0.

The curvilinear function in Figure 7 is negatively sloped, i.e., the bigger the shape parameter, the smaller the left tail. Its slope is variable, steeper over smaller shape parameters characteristic of the less well educated. Figure 7 shows that the speculation, that the greater dispersion of the proportion of small incomes among the less educated, follows from Conditions #1 to #3. It only remains to be seen just how closely change in distribution shape is related to change in the proportion of small incomes.

The Correlation between the Slope of the Curve in Figures 7 and 8 at the Shape Parameters of Education Groups and the Standard Deviation of the Proportion of Small Incomes by Level of Education

All that remains to be shown is that the year effects on the shape parameter of all education groups, displayed in Figure 6, which yielded only a slight improvement in the fit of the gamma pdf to the 165 partial distributions, are sufficient all by themselves to produce the greater dispersion of the proportion of small incomes among the less well educated. There are two ways that this demonstration can be made. The first is to correlate the slopes of the curve of Figure 7 at the point of intersection with the shape parameters of each education group, α_i, with the standard deviation of the proportion of small incomes by level of education from 1963 through 1995. The second method is to correlate the proportion of small incomes with the left tail areas of the gamma pdf with shape parameter $\alpha_i + \alpha_i$.

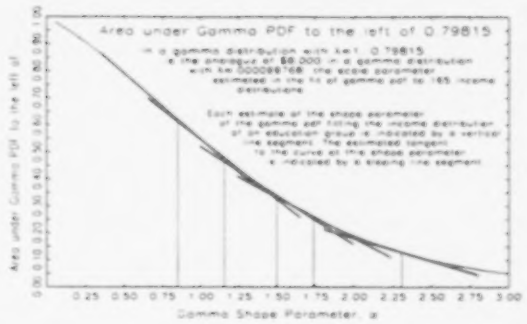
Area under Gamma PDF to the left of 0.79815
Area under Gamma PDF to the left of
0.25 0.50 0.75 1.00 1.25 1.50 1.75 2.00 2.25 2.50 2.75 3.00
Gamma Shape Parameter, α

Figure 8

Figure 8 is Figure 7 with additional information. The estimate of the shape parameter of the gamma pdf fitted to the income distribution of each education group, α_i, i.e., net of year effects, is marked by a vertical line segment. At the intersection of the vertical line segment with the curve is a sloped line segment. The slope of the line segment of education group i, call the slope b_i, an approximation to the tangent of the curve at the estimated shape parameter of education group i. Change in the size of the left tail can be approximated in Figure 8 by the expression $b_i\alpha_i$. b_i is estimated by evaluating the curve at .01 to the left of α_i and .01 to the right of α_i and calculating the slope between the two points. The approximate tangent line segment is drawn from .5 to the right and .5 to the left of the estimated shape parameter so that its end points are distinct from the curve in Figure 8. The numerically estimated derivatives of the curve at each estimated shape parameter are:

highest level of education	slopes of curve in Figures 7 and 8 at estimated shape parameter	standard error from 100 bootstrap resamplings
at most elementary school	-.48781	.00395
some high school	-.44268	.01000
high school graduate	-.36215	.01185
some college	-.30075	.01339
at least college graduate	-.17045	.01005

These derivatives are correlated -.95716 with the standard deviations of the proportion of small incomes (defined as from $1 to $8,000 in 1989 dollars) from 1963 through 1995 in Figure 1. This correlation is strong confirmation that the sensitivity of the proportion of small incomes to small changes in the shape of an income distribution is strongly and inversely related to the shape parameter of the gamma pdf fitted to it.

Correlation Between Actual Proportion of Small Incomes and Proportion Expected Given Constrained Gamma PDF Fit

There is an even stronger possible confirmation of this proposition than the demonstration of the close correlation between the slopes of the curve in Figure 8 and the standard deviations of the proportion of small incomes. It is the correlation between the estimated proportion of the left tail of the gamma pdf with shape parameter ($\alpha_i + \alpha_t$) with the actual proportion of small incomes in an education group in a year. α_i is the estimated shape parameter of the ith education group, net of year effect, and α_t is the estimated component of each education group's shape in year t. α_t is the same for all education groups, guaranteeing the equal perturbation of each education group's shape parameter in each year. This correlation is over 165 (= 33 years x 5 education groups) proportions of small incomes. The 165 empirical proportions with small incomes, by level of education, are correlated .97280 with the area of the left tails of gamma pdfs with shape parameter ($\alpha_i + \alpha_t$).

So the speculation of this paper that the greater dispersion of the proportion of small incomes of the less educated in Figure 1 derives from the more convex down shape of their income distributions is correct. This paper has also demonstrated that the shapes of all income distributions fluctuate in a way that is correlated with fluctuations in the national median of personal income (Figure 2), a measure of the impact of the business cycle on people. It appears then that the proportion of small incomes among the less educated rides a roller coaster over the business cycle, shooting up at the onset of a recession, relative to more educated people, but also plunging downward just as vigorously when the economy expands. Recessions increase the proportion of small incomes and business expansions decrease that proportion more among the less educated than among the more educated.

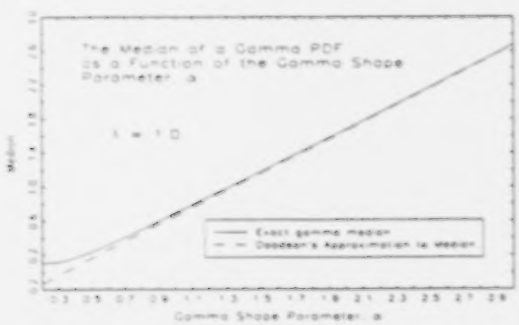
The Median of a Gamma PDF
as a Function of the Gamma Shape
Parameter, λ
λ = 1.0
Exact gamma median
Doodson's Approximation to median
Gamma Shape Parameter, α

Figure 9

Forecasting of the Proportion of Small Incomes One Year Ahead Contingent on Knowledge of Income Median One Year Ahead

Although the proportion of small incomes among the less educated is noisy, it can be reliably forecasted, contingent on a good forecast of their median income. The median and area of the left tail of distributions that are at least approximately gamma distributed are closely related. The curve in Figures 7 and 8 can be well approximated by a line. For some ranges of distribution shapes, such as those of nonmetro people with at most an elementary school education, it is difficult to distinguish a linear approximation from the curve itself. See Figure 8. For gamma pdfs shaped like this group's income distribution, the area of the left tail is a nearly linear function of the gamma shape parameter.

The shape parameter of gamma pdfs with scale parameter constrained to a single common value is also quite closely and linearly related to the median of the gamma pdf, as you can see in Figure 9. Doodson's approximation to the gamma median (Salem and Mount, 1974) is:

$$\frac{(3\alpha - 1)}{3\lambda}$$

So dropping the gamma shape parameter in between a close, linear relationship between left tail and median should not be surprising. See Figure 10. The r^2 of this OLS regression is .978, a very close fit. So even though the proportion of small incomes among nonmetro people with at most an elementary school education may be more dispersed, if the median income of nonmetro people with at most an elementary school education is known, the

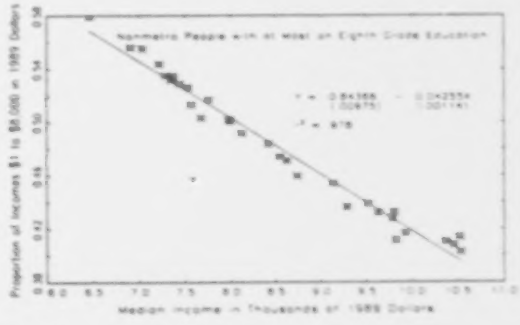

Figure 10

proportion of small incomes among them can be accurately estimated.

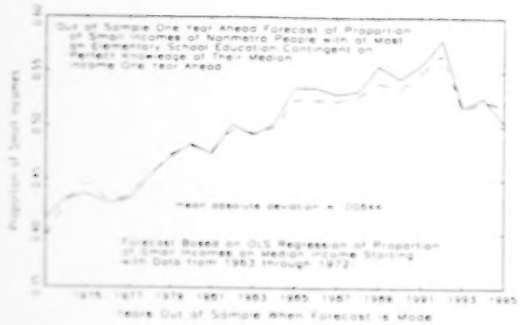
Out of Sample One Year Ahead Forecast of Proportion of Small Incomes of Nonmetro People with at Most an Elementary School Education Contingent on Perfect Knowledge of Their Median Income One Year Ahead
Mean absolute deviation = .00644
Forecast Based on OLS Regression of Proportion of Small Incomes on Median Income Starting with Data from 1963 through 1972
Proportion of Small Incomes
1973 1975 1977 1979 1981 1983 1985 1987 1989 1991 1993 1995
Years Out of Sample When Forecast is Made

Figure 11

Figure 11 shows that the proportion with small incomes among nonmetro people with at most an elementary school education can be reliably forecasted. Figure 11 shows one year ahead out-of-sample forecasts. These forecasts are based on an OLS regression of proportion with small incomes among nonmetro people with at most an elementary school education on their median income. The original sample is ten years of data from 1963 through 1972 inclusive. The 1973 forecast is made with these estimated coefficients and the true 1973 median income of nonmetro people with at most an elementary school education, i.e., a using a perfect forecast of the 1973 income median. Then the regression is re-estimated with 1973 data, and the 1974 median is used to forecast the 1974 proportion with small incomes, and so on through 1995. The mean absolute deviation (error) of this procedure is .00644, less then a percentage point. This exercise makes clear that there is negligible additional error in forecasting the proportion of small incomes among nonmetro people with at most an elementary school education, the education group with the noisiest proportion, contingent on a forecast of their median. Thus, if the forecast of the median is accurate, the forecast of the proportion of small incomes, prepared this way, is almost as accurate.

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FORECASTING TECHNIQUES

Chair: Karen S. Hamrick
Economic Research Service, U.S. Department of Agriculture

The Expanding Constituencies for Weather Information,
Jeanne Kelly, Jennifer Jarratt, and Joseph F. Coates
Kanawha Institute for the Study of the Future

Bankers' Probabilistic Judgements of Short-term Trends in Long-term Loan Rates,
Ted Covey, Economic Research Service, U.S. Department of Agriculture

Continuous Numerical Continuation,
Foster Morrison & Nancy L. Morrison, Turtle Hollow Associates, Inc.

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THE EXPANDING CONSTITUENCIES FOR WEATHER INFORMATION

Jeanne Kelly, Jennifer Jarratt, and Joseph F. Coates
Kanawha Institute for the Study of the Future
Washington, DC

The National Weather Service/NOAA is continuing to upgrade its technological base and its technological competence, and is reorganizing its resources and sites. As a result, the weather information the NWS delivers is more immediate, more technologically sophisticated and has greater depth and coverage. As these new capabilities of the NWS come into place, there are two questions central to its planning and to the ongoing evaluation of its effectiveness. One is, what new actual or potential users, constituents, or applications will there be for its services and information? The other question is how can the NWS continue to make the best use of its new and emerging capabilities in ways that will benefit constituents and the nation's economic health?

It is assumed that even as the NWS is changing, upgrading its capabilities, and reorganizing, so too are the various sectors of the economy. Constituent demands for information are likely to be more complex and more specific. On the other hand, some constituents may not yet be prepared for, or aware of, the more sophisticated information delivery systems that are becoming available.

The Kanawha Institute for the Study of the Future assisted the National Weather Service in looking at these issues by studying the present and future needs for weather data and information of business and industry, the infrastructure, agriculture, forestry, fisheries, health, emergency management, and various other constituents. By studying the trends and forces shaping change in each sector, it was clear that many constituents have changing and expanding needs for weather data and related information.

Overview

- As the U.S. economy becomes more complex and fine-tuned, the need for more timely and reliable information of all sorts becomes acute. Weather forecasts are an important source of information that has nearly universal applications.
- Three areas are conspicuously underserved with pertinent weather information:
  - small operations, both public and private, such as small businesses and farms, and local public institutions
  - rural areas in general
  - the health sector
- People, as private citizens, find their recreation, travel, and other activities strongly influenced by weather, especially as activities must be fitted into tight schedules.
- As work sites are decentralized and as more people choose to engage in telework or work independently on the road, they will have a greater need for regular, updated weather information that can affect their work and movements.
- Widespread discussion of global climate change and the perception of increasing extremes in weather make this period of increased weather awareness a good time for the NWS to promote its services.
- Private weather services are constantly seeking new and creative ways to make NWS data relevant to clients through integration with economic data. A close relationship between these services and the NWS could be beneficial to all sides in helping the business community.
- The proliferating use of public and private data screens and mobile electronic units could provide NWS many new opportunities to deliver its weather information directly to people doing on-the-spot planning and decision-making.
- As more operations work on a 24-hour basis, needs are expanding for integrating weather data into the system as a continuously updated stream of information.
- New technologies, such as intelligent highway systems or cockpit navigation systems, will call for:
  - new modes of delivery of weather information, such as continuous delivery, as well as ad lib inquiry by drivers and pilots
  - the combining of raw data from many sources, i.e., both passive collectors, such as sensors and gauges, and complex NWS systems, such as satellites and automated stations
  - the seamless integration of data into complex systems

This will require more joint programs between the NWS and teams from other fields.

What the Weather Service can supply will change constituent expectations

The emerging technological capabilities of the Weather Service will include:

- more timely and accurate information, forecasts, and warnings
- more regional and geographically specific forecasts and warnings
- greater coverage and more detail in coverage
- integration of weather data and information into more accessible and continuous visual display
- greater access to data and information through online and network delivery
- partnerships within NOAA and with other federal agencies, such as NASA, that would expand weather information to include seasonal and long-term forecasting, and space and solar forecasting

Timeliness

Historically, the National Weather Service has provided forecasts and warnings at whatever time interval was technically possible or appropriate. Users welcomed the advances in accuracy, timeliness, and specificity of these forecasts. It seems likely that with the expanding use of information technology and the computer-aided smartness of many systems, Weather Service data will become desirable as a data stream rather than as a series of forecasts, or at least as a continuous supply of forecast information that can be fed into the information flows of many organizations and systems. If this occurs it is likely to change the relationship of the Weather Service with its constituents in many ways, several of which are explored in this report.

Weather phenomena considered in this report

Weather types and weather-caused or derived phenomena were drawn from the Weather Service's own descriptions of important phenomena. Thirty-three were considered in relation to geographic factors, coastal versus inland areas, urban settings or rural, high, medium, or low-lying terrain, and the availability of water. The basic list was not inclusive of all the types and variations on weather. For example, harsh winters are universally understood, but may mean different types of weather, depending on how far north or south the observer might be.

Specifically, we considered 13 time intervals from climatic down to hour, minute, seconds, and continuous.

Scope of users of weather information

Starting with the US Industrial Outlook and the Standard Industrial Classification Manual on a category or category analysis we identified possible interests in weather. That preliminary investigation of what kinds of weather might affect different businesses, industries, units of government, was followed by interviews to establish what interest there might be in earlier, more complete, or different information about weather.

Exhibit 1 Impact Points of Weather Conditions on Manufacturing, suggests the broad scope of consequences of weather on manufacturing.

Weather affects manufacturing by:

- Reducing raw material, parts availability, quality
- Interrupting deliveries
- Closing plants, damaging equipment
- Cutting or reducing power, water
- Determining pollutant emissions release
- Delaying, preventing outdoor work
- Lowering or stopping labor productivity
- Raising or lowering product demand

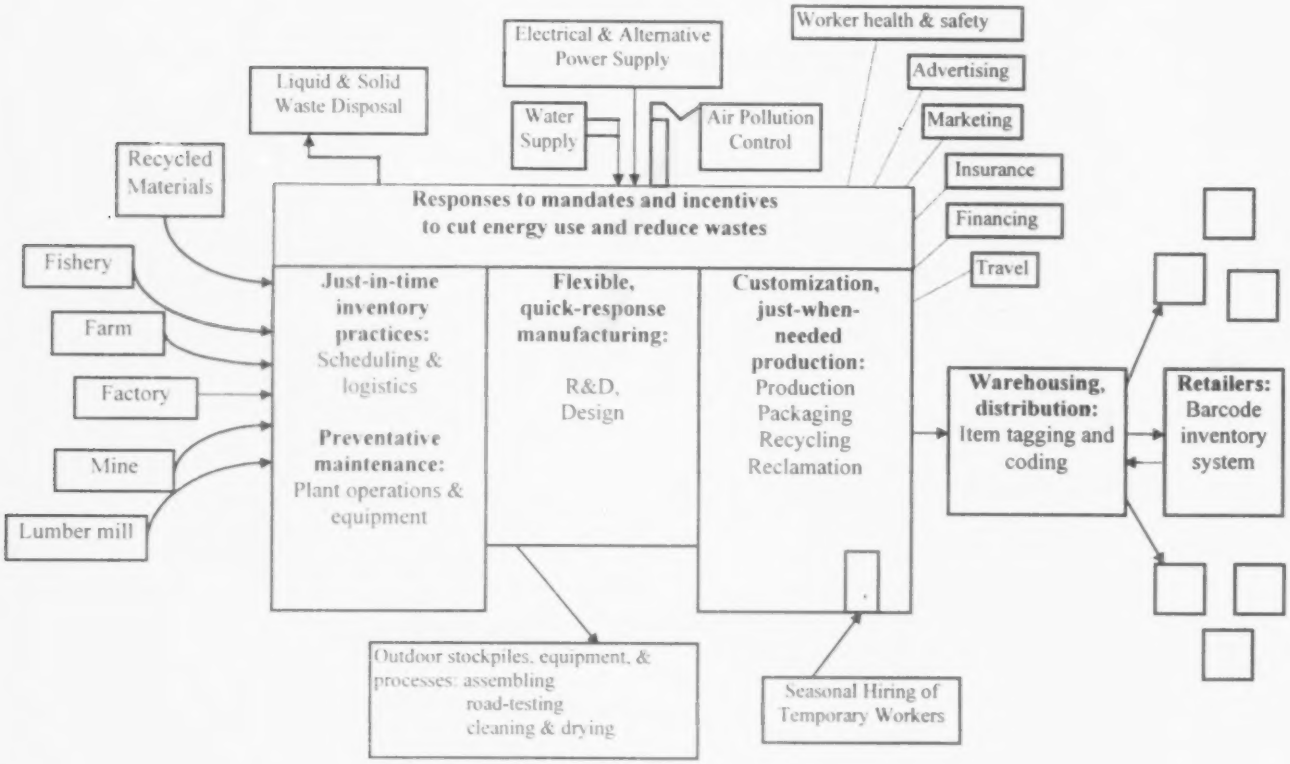
Ways for the National Weather Service to help:

- Make localized weather warnings easily available, so a factory can decide whether to close or not.
- Help businesses quickly get worldwide, nationwide, and local weather information, such as for truckers planning routes.
- Help manufacturers get regionalized seasonal forecasts, such as for planning production levels of swimwear.
- Work with software engineers doing simulations and modeling to find new ways to integrate weather data in research and analysis, such as in environmental analysis.
- Work with private weather services to identify and to fill gaps in weather information needed by businesses.

Knowledge of near- and long-term weather conditions can now help manufacturers reduce costs, improve efficiency, and gain a competitive edge in their industry. In the future such knowledge and the ability to use it will become a necessity. Weather forecasting can make an economic difference to manufacturers increasingly affected by:

- **Systems integration.** Intense competition within most industries has forced manufacturers to hold down overhead costs by running tightly integrated performance systems. This involves use of just-in-time inventory and delivery, flexible production practices, and alliances with retailers using quick response (to consumer demand) systems.

Exhibit 1 Impact Points of Weather Conditions on Manufacturing Process


Electrical & Alternative Power Supply
Worker health & safety
Liquid & Solid Waste Disposal
Advertising
Water Supply
Air Pollution Control
Marketing
Recycled Materials
Insurance
Responses to mandates and incentives to cut energy use and reduce wastes
Financing
Fishery
Travel
Farm
Just-in-time inventory practices: Scheduling & logistics
Flexible, quick-response manufacturing: R&D, Design
Customization, just-when-needed production: Production Packaging Recycling Reclamation
Factory
Warehousing, distribution: Item tagging and coding
Retailers: Barcode inventory system
Mine
Preventative maintenance: Plant operations & equipment
Lumber mill
Outdoor stockpiles, equipment, & processes: assembling road-testing cleaning & drying
Seasonal Hiring of Temporary Workers
1 Seasonal availability of parts, raw and recycled
2 Delivery: routing, temperature & humidity control
3 Production continuity
4 Environmental concerns
5 Supporting services
6 Shelf life: delivery, distribution & storage
7 Product demand

- **Globalization.** The production process now fits into interconnected, globalized networks. A manufacturing operation must often obtain its parts and raw materials from many parts of the world and deliver goods to international customers while meeting global standards for environmental sustainability. Vulnerability to weather in developing countries and the need to shift production sites to meet seasonal changes must be taken into account.
- **Quality taken for granted.** Demand for high value means to achieve customer satisfaction, manufacturers must use the best materials to produce and deliver high quality goods on time.
- **International competitiveness.** Worldwide competition increases pressure to achieve a competitive edge. This includes on-time delivery and high quality, often customized, products to suit regional, local and even individual differences.
- **Smartness.** Products and materials are now built to monitor and adjust to external conditions, such as noise, temperature, and movements, which allows flexibility in responding to weather information.

- **Downtime.** Weather forecasts can make a difference in preparing for floods, tornadoes, and blizzards, and preventing disruptions, accidents, and property losses which cause prolonged downtime.

As manufacturers must operate under these conditions and demands, so must the National Weather Service and other government agencies if they are to support the nation's economic well-being.

Conclusions

The different sectors of the economy and society are sensitive to weather information in varying degrees. It is worthwhile here to summarize those differences. How the Weather Service works with the various sectors may well depend on their differing uses of weather services and products, and their emerging needs for information and data.

Business and industry are primarily interested in information on weather impacts that:

- shape demand for goods and services
- interfere with the speed and efficiency of processes, such as distribution
- significantly increase or decrease the cost of doing business, such as severe weather events occurring at critical times, or a long spell of fine, clear weather
- affect supply of raw materials

Where business and industry *should* be interested in weather information—an opportunity for the Weather Service—is in information that:

- improves the smartness or intelligence of a business process, which requires that data be fed in continuously, such as in logistics scheduling
- adds to competitive advantage, such as timely warning of weather situations in any locality where they have operations, including overseas
- can add value to a purchase or the use of a service—weather information at point of sale or choice

The players in **the infrastructure** are primarily interested in information on weather impacts that:

- are severe enough to disrupt the continuity and efficiency of the system, such as flooding, heavy snowfall, or perhaps solar disturbances
- will put people at risk, such as thunderstorms and tornadoes
- will affect planning, scheduling, and routing

Where the infrastructure players *should be* interested in weather information—an opportunity for the Weather Service—is in information that:

- enhances the intelligent capabilities of the system, such as smart transmission wires and intelligent highways
- adds knowledge to the long-term questions of maintenance, repair, and replacement of equipment and maintenance, such as an integration of weather information and sensing data on the degradation of bridge structures
- allows for the opportunity to re-allocate resources in the system in the event of large impacts on any particular part

The health system is perhaps the most neglected user of weather data and information. Actors in the health system, including those involved with public and occupational health and safety, are primarily interested in weather information that:

- warns of threats to public safety or public health—by influencing the spread of a disease or with the potential for causing injury or death
- changes the frequency of needs for health care, such as snow and ice leading to more emergency room visits
- warns of impacts on specific diseases, such as the effect of UV radiation on persons with cataracts

There is no doubt that the system itself and people in it, such as patients, could get more value from weather information. Where the health care system *should be* interested in weather information—an opportunity for the Weather Service—is in information that:

- alerts physicians and sufferers to specific events that will affect a particular disease or condition, allowing them to prepare for or prevent adverse effects
- contributes to research on the best ways of managing diseases and conditions
- contributes to the prevention of lost work days in ways that can be measured in dollars and cents
- aids in the long-term study of changing weather and climate patterns that influence the spread of diseases and the introduction of new ones
- permits more efficient rescheduling or re-allocation of resources in the system, particularly important for emergency rooms and emergency response teams

The agricultural and fisheries sectors are the most intimately connected with weather information, short- and long-term, local, regional, and global. Large

businesses in agriculture are among the most sophisticated users. Agricultural users are primarily interested in information that:

- affects the timing of processes, such as planting and harvesting
- produces timely warnings of severe weather events that are specific enough to help prevent damage
- contributes with seasonal information to planning of crops and products
- advises of conditions that could affect the health of plants and animals, and thus affect yield

Where agricultural users *should be* interested in weather information—an opportunity for the Weather Service—is in information that:

- makes a process smarter, such as bringing weather data into integrated pest management
- offers seasonal and long-term information of weather cycle changes that are substantial enough for farmers to change their entire crop and product strategy
- creates a smarter crop or animal, by being incorporated into genetic research
- reports on the global agricultural picture and is aimed at sectors particularly important to U.S. agriculture, such as the prospects for harvest size in key crops like corn, rice, cotton, and so on
- helps the agricultural sector achieve greater flexibility in crop choices and in approaches to farming
- helps fisheries understand implications of weather forecasts for fish and shellfish development
- provides local, specific, and regional historic and forecast data on forests, perhaps by creating a weather profile for an infant forest in its first 10 to 20 years

Emergency management professionals and volunteers need weather information at all points in the disaster continuum. This includes:

- historical data which can help analyze and reduce community vulnerabilities
- accurate, easily grasped information which can allow time for assessing and preparing for emergencies
- continuous, localized information which can help organize disaster recovery
- specific data tailored to the needs of communities recovering from disaster, such as precipitation forecasts after flooding

What emergency managers *should want* added to the information they receive is:

- graphic displays showing localized severe weather impacts
- open lines with forecast centers allowing two-way communication during emergencies
- quick access to easy-to-understand forecasts and warnings through varied methods of communication
- formats that allow integration of the data into software programs and other valued-added systems such as geographical information systems
- coordination with warnings and forecasts provided by other weather services and the media to avoid confusion
- faster warning times on weather threats affecting heavily populated coastal areas to offset lengthier evacuation times
- heat wave warnings

Many **other users** are interested in weather information for specific purposes. Their current demand for weather information includes information that:

- helps them manage large projects or specific events, such as big engineering enterprises, or sporting events
- warns of threats to the efficient operation of social systems, such as education, voting, and public meetings
- helps them preserve treasures, such as historic buildings
- helps them manage wildlife and prepare for possible problems, such as fire
- helps predict demands on services, such as recreational areas or hospitals

These users *should be* interested in weather information—an opportunity for the Weather Service—that:

- helps them increase the smartness of their operations, such as including weather data in construction scheduling programs
- enhances their customers' use of recreational opportunities, by providing weather data and advice at point of game to golfers, or at head of trail to hikers or snowmobilers
- supplies long-term and seasonal information for planning, including historical data
- indicates when rescheduling or reallocation of resources might be the most useful response

- is continuously available to measure degradation of buildings or environments, through sensors and satellites
- prevents accidents by delivering just-in-time warnings or advisories of danger to risk-taking users, such as cross-country skiers, hang-gliders, hunters, backpackers, and mountain climbers
- can be projected on built-in displays and signboards at large projects and recreational areas for worker and user safety

The remaining large category of users consists of **people who as individual citizens** must use weather information to make their own decisions independent of institutions, systems, or organizations. Individual users are in a dual role, as members of families and as participants in institutions through a work or membership role. Their current use of weather information is varied, and includes an interest in information that:

- warns or advises of potential threat to their lives, homes, property, and health
- supplies data for daily decisions about activities, travel to work, clothing, and many other things
- contributes to quality of life, and personal well-being
- supplies an activity, an interest, and can help make a worthwhile social contribution—especially for hobbyists, volunteer weather observers, and storm watchers

These individual users *should be* interested in weather information—an opportunity for the Weather Service—that:

- enables them to make their own choices about work, travel, safety, and health, by knowing more about the influence of weather on things important to them—particularly important to distributed workers who become their own health and safety inspectors
- allows them to manage chronic diseases or conditions more effectively
- gives them new information to manage their interactions with larger systems, such as the health care system, education, and employers
- provides key information at the point of making a personal decision, such as when to take a ski vacation or have surgery

Based on these conclusions about weather information users, the following recommendations are made.

Recommendations

1) Work with designers and engineers at the research and development stage of new devices and systems in order to find mutual ways to integrate weather information into, for example, the construction of ports, harbors, bridges, cockpits, transit systems, waste treatment systems, or power transmission facilities.

2) Find ways to give greater saliency to weather forecasts. For example, reflecting the high value of imagery to users of weather, the Weather Service could do two things:
   - develop a quantitative system scaled 1-5 or 1-10, parallel to the Beaufort scale, perhaps one for winter and one for summer use
   - develop weather profiles which would draw upon historical examples or illustrations to bring home the message

   Scales could be augmented with specific imagery drawn from the level of event in question. For example, it might be reported that an upcoming snowstorm will register 4 on the Boezi scale, which would put it in a league with the December 1992 snowfall. Where practical, such as on TV, forecasts could be accompanied by footage of that particular storm.

3) Seek feedback on the effects of removing or changing services from those affected. Upgrading or automating weather collection systems may cut off certain capabilities, such as the new GOES satellite which lost volcanic ash detection capability, Doppler radar which may miss important information in mountainous terrain which ground stations had gathered previously, etc.

4) Make weather data available and accessible to developers of software programs which add visual or audio aids to make the information user-friendly for utility dispatch centers, air traffic controllers, and others.

5) It is important for the Weather Service to introduce continuously updated weather information into new places where it can have an effect on public attitudes and behavior, and to bring it to groups of people where it can influence their decisions. These places and people include:
   - *Point of decision or point of sale*—to bring important information to people who are at the point of either buying something, deciding on travel choices, or interacting with the environment in a possibly unsafe way. This access to information could be in a travel agent's office, in an airport, at a public

kiosk, at the head of a trail on Mt. Rainier, overhead as a highway display, or displayed inside a vehicle or boat.

- *Sites with sensors and measuring instruments*—so that continuous weather data can be used to determine the effects of the environment on physical structures and natural systems, or managed systems such as fields and forests.
- *Businessmen, planners, and managers*—to bring historical data and long-term forecasting to the planning table so that it is incorporated in the planning and management of any and all systems. These might be a highway project, a start-up business, the prevention of a disease outbreak, or the future of a park.
- *Work sites*—so decisions can be made on when to schedule a concrete pour or fit a dome on top of a building.

6) The Weather Service should explore and experiment with the convergence of its integrated data systems with the expanding smart information systems in the private and public sectors. The NWS may be able to integrate continuous weather data into intelligent systems that can use the data to operate more efficiently. Examples would be the power transmission grids, where transmission efficiency will be critical as utilities become more competitive under deregulation, and the intelligent highways that will be developed over the next decade.
   - The other aspect of the Weather Service's improving capabilities that will be significant to many users is the ability to provide micro-scale forecasts for a particular locale or small region.

7) The Weather Service should educate the public and professionals to be able to interpret and use weather information more effectively in managing health, lifestyles, emergencies, potential threats, and opportunities. To that end, we suggest the Weather Service join with the CDC (Centers for Disease Control) or the AMA (American Medical Association) to publish newsletters on the connection between health and weather. Physicians and public health organizations are aware of the relationship between weather and health but have not systematically, much less comprehensively, integrated this into their thinking. They are not always able to give advice to patients with weather-sensitive ailments.

8) The question of whether the Weather Service is speaking the same language as its audiences in its forecasts and warnings is important because it affects the power of the messages and their acceptance. The NWS should review whether its services and products could be presented in a way more immediately usable. An example is the Weather Service's use of probabilities. Exactly how to make decisions based on those probability assumptions may have to be explained to some users.

9) It is important for the Weather Service to expand its dialog with constituents, since each can learn from the other. Those who could benefit from weather data do not always know how to access or use it to fit their own needs. For some the value of using available data is potentially high, but this needs to be demonstrated through outreach or demonstration projects so this value can be seen and measured. An example of this is the electric utility industry, which uses NWS and private weather service forecasts but is not always able to coordinate them.

10) Make explicit attempts to provide low probability long-term forecasts, such as of a long winter or hot summer. These can be of significant use in planning.

11) Pioneer approaches to expanding information available to meet needs of neglected markets, such as businesses needing localized or more continuous information.

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The Kanawha Institute is located at 3738 Kanawha Street, NW, Washington, DC 20015.

BANKERS' PROBABILISTIC JUDGEMENTS OF SHORT-TERM TRENDS IN LONG-TERM LOAN RATES

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Agricultural bankers' investment decisions reflect their expectations of future interest rate trends as well as the degree of confidence they place in their forecasts. For example, profit-maximizing bankers adjust the relative durations of their portfolios' assets and liabilities according to their expectations of future trends in interest rates (Rose). Bankers also reflect their expectations of interest rates trends when setting the size of the fixed to variable rate premium on agricultural loans.

Probabilistic forecasts are forecasts accompanied by numerical statements expressing the degree of certainty the forecaster has in his prediction. A banker making a probability forecast issued with about a 90 percent degree of confidence will elicit a very different response by forecast consumers than the same prediction issued with a 10 percent degree of confidence.

Interest rate forecast error has consequences. Ellinger and Barry showed that a sizable portion of agricultural banks had significant high or low duration gaps, leaving them exposed to unanticipated changes in interest rates. Belognia and Gilbert showed that the greater this gap, the greater the agricultural bank's likelihood of bankruptcy due to interest rate forecast error.

The extent to which probabilistic forecasts correctly anticipates the events that ultimately occur is called *external correspondence*. Probabilistic forecasts are said to exhibit good external correspondence when events that are assigned probabilities close to one occur frequently, and those assigned probabilities near zero occur rarely (Yates 1982). The better the external correspondence, the more likely it is that the decision based on the forecast will turn out well (Yates and Curley). Brier's Probability Score is a measure of external correspondence which lets decision makers assess and contrast different qualities of probabilistic forecasters.

The Ninth Federal Reserve District Bank (Minneapolis) collects and reports agricultural bankers' expectations of a number of key economic and financial variables, including the bankers' expectations of future trends in interest rates on farm loans (Board of Governors). This paper evaluates and contrasts the external correspondence of the probability forecasts issued by agricultural bankers regarding future short-term trends in interest rates on long-term real estate farm loans over two different monetary regimes.

Brier's Probability Score PS

Suppose that on a particular occasion 'i' event 'A' can occur in only one of K possible outcomes. The probabilities assigned to each possible outcome k are f_1, f_2, . . . , f_K that the realized outcome or event will occur in outcome 1, 2, . . . , K respectively and $0 \leq f_k \leq 1.0$. The greater the forecaster's confidence in k's outcome, the larger f_k. The K possible outcomes are mutually exclusive and exhaustive so that:

$$(1) \qquad \sum f_k = 1.0$$

where k = 1, 2, . . . , K. In order to assess a forecaster's accuracy in assigning probabilities to different possible outcomes, Brier proposed a probability score PS:

$$(2) \qquad PS = \sum (f_k - d_k)^2$$

where the outcome index d_k takes the value '1' if the event occurred in class k and '0' if it did not; and where $0 \leq PS \leq 2.0$. The forecaster's objective is to minimize PS.

The higher the probability assigned ex ante by the forecaster to the ex post actual outcome k, the lower PS. The optimal result, PS = 0, results from the forecaster having assigned a probability of absolute certainty (f = 1.0) to the realized event's occurrence. Forecast error is the result of failing to assign complete certainty to the realized outcome and results in $0 < PS \leq 2.0$. The worse possible result, PS = 2.0, results from assigning a probability of absolute certainty ($f_k = 1.0$) to an event which did not occur ($d_k = 0$).

Individual probability scores for each event i can be aggregated and averaged for an entire data set of N probability forecasts, resulting in what Brier defined as the mean probability score for N such occasions:

$$(3) \qquad \overline{PS} = 1/N \sum \sum (f_{ik} - d_{ik})^2$$

where i = 1, 2, . . . , N. The mean probability score $\overline{PS}$ has the same bounds and interpretations as the probability score PS.

Bias and Slope Scores

The bias statistic $(\bar{f} - \bar{d})$ reflects the difference between the average probability assigned to a possible outcome's occurrence and its relative frequency over the forecast period.

The optimal "bias" value is 0 and can range from 1.00 to -1.00. A positive bias indicates that on average bankers assign too high a probability to this outcome, while a negative bias indicates bankers on average assign too low a probability. The bias statistic reflects the extent to which the judge's assessments are generally too high or too low.

The greater the familiarity of the forecaster with the targeted event, the smaller the bias. However, bias could result from the forecaster's perception of an asymmetric loss function. If failure to prepare for higher loan rates is viewed as more serious than failure to prepare for lower loan rates, then there would exist a larger positive bias regarding bankers' assessments of higher than lower loan rates.

The term "slope" (Slope = $\bar{f}_1 - \bar{f}_0$) is the difference between the average probability assigned to a particular event's occurrence given its occurrence and the average probability assigned to that event's occurrence when it did not occur.

Slope ranges from -1.00 to its "ideal" value of 1.00. In the ideal case, the judge always reports $f = 1$ when the target event is going to occur and $f = 0$ when it is not. The larger the slope, the better the forecaster's resolution. Greater slope leads to a smaller mean probability score. A higher slope indicates better judgement of the future and may be a reflection of different incentive structures or the quality of the information at the forecaster's disposal. One would expect a lower slope score in situations where forecasting is relatively more difficult, when incentive structures do not encourage discrimination ability, or when information sources are less reliable.

Outcome Variance Var(d)

Murphy offered a simple measure of the volatility or variance of the different possible forecasted outcomes an event may take. Murphy defined the variance of each outcome as:

$$(4) \qquad \mathrm{Var}(d) = \bar{d}(1 - \bar{d})$$

Variances for each of the three outcomes are calculated for both periods and presented in Table 4.

Calculation of Murphy's outcome variance statistic is useful for comparing the relative difficulty in forecast contests. The assumption is that the greater the variability of a particular outcome, the more difficult the forecasting problem and thus the greater the mean probability score.

Data

The data, quarterly interest rates on new long-term real estate farm loans made from the first quarter of 1974 (1974:Q1) through the third quarter of 1985 (1985:Q3) and bankers' expectations thereof, are taken from surveys of Upper Midwestern agricultural bankers conducted by the Ninth District (Minneapolis) Federal Reserve Bank (Board of Governors).

The individual bankers were surveyed each quarter as to whether they believed loan rates made at their bank over the next quarter would be lower, about the same, or higher than the previous quarter. Individual bankers do not issue probability forecasts for the Ninth District, but simply "check off" on the survey which of the three trends is most likely to occur within their particular loan market over the next quarter. The individual banker's responses are aggregated and reported by the Fed as the percentage of all bankers expecting long-term real estate loan rates to be either lower, stable, or higher by next quarter. This paper uses these group percentages as group probability forecasts of quarterly interest rate trends for the Ninth Federal Reserve District.

The Minneapolis Fed's time series of quarterly average loan rates is differenced and then categorized as "lower, stable, or higher." The Fed does not define or distinguish these three categories, leaving it to the researcher to determine how large a quarterly change in interest rates must occur in order to be classified as "higher or lower" rather than "stable." It was thus necessary to develop a rule to convert this quantitative series into a qualitative time series of the three possible outcomes.

Kolb and Stekler evaluated forecasters of short- and long-term Treasury interest rates over the same time period as this paper. They found that these forecasters had a 70-basis point standard deviation in their forecasts. They therefore required at least one-half of a standard deviation or 35-basis point rise (fall) in interest rates for a change in interest rates to be classified as higher (lower). Any change less than this was classified as stable.

This paper follows Kolb and Stekler's rule in classifying

quarterly changes in intermediate-term interest rates on agricultural loans as lower, stable, or higher. Any quarterly change in interest rates of 35 basis points or less is regarded as "stable," otherwise as "higher" or "lower."

The data series of probability forecasts and their respective outcomes are divided into two periods. The first period covered the first quarter of 1974 through the third quarter of 1979. This was a period when the Federal Reserve attempted to simultaneously control both the money supply and interest rates. The second period examined started with the fourth quarter of 1979 through the third quarter of 1985. This was the period where the Fed chose to focus its control on the money supply in order to bring double-digit inflation under control.

Reference Points for Probability Forecasters

Yates (1988) suggested two points of reference for contrasting probability forecasters: (1) the *uniform forecaster* who behaves as if all events are equally likely ($f_k = 1/K$ for $k = 1, \ldots, K$); and (2) the *relative frequency forecaster* who always offers f_k = the future relative frequencies for each of the three possible outcomes. Yates recommended the relative frequencies of the forecast period be used, rather than past relative frequencies. This results in unbiased forecasts and allows a test of the "forward-lookingness" ability of the bankers.

In this application with K=3, the uniform forecaster issues $f = 0.33$ for all three outcomes at all times i. For the uniform judge with $K = 3$, the multiple or total probability score $= 1 - (1/K) = 0.67$.

In the first period, 1974:Q1-1979:Q3, the relative frequency forecaster issued $f = 0.04, 0.57, 0.39$ for the likelihood of lower, stable, or higher for each quarterly trend. Similarly in the second period, 1979:Q4-1985:Q3, the relative frequency forecaster issued $f = 0.42, 0.29, 0.29$.

Contrasting Bankers and Constant Probability Assessors

Contrasting the total mean probability scores indicates bankers outperformed the uniform and relative frequency forecasters in assigning probabilities to quarterly trends in long-term real estate loan rates during the first period (Table 1). Bankers clearly outperformed the uniform forecaster in all three categories (lower, stable, and higher) and the relative frequency forecaster in assigning probabilities to stable and higher categories. Bankers' superior resolution skills more than offset the advantage of unbiasedness of the relative frequency forecaster.

However, exactly the opposite conclusions are drawn in the second period (Table 1). Here the total probability score for bankers exceeds even that of the uniform forecaster in all three categories.

Contrasting the bankers' relative performance between the two periods, the second period in which interest rates were influenced by new and unfamiliar monetary policy resulted in more than doubling of the bankers' total probability forecast error. The largest increase in forecast error was in bankers' ability to assign probabilities to declines, where the mean probability score increased by a factor of six. This increase may well be due to the greatly increased variance in lower outcomes, which also increased by a factor of six between the two periods (Table 4). Mean probability scores for "stable" doubled and for "higher" increased by 22 percent. However, variance measures for these two outcomes were lower in the second period than first period. Thus the decline in bankers' probability forecast performance for these two outcomes between the two periods must be due to factors other than outcome volatility.

Bankers' Bias and Slope Measures

In the first period, bankers showed relatively little bias in their assignments of probabilities to the three possible trends (Table 2). The highly volatile second period saw large increases in the bias scores for "down" and "stable." However, a consistent theme that one may infer from comparing the two periods is that bankers assign too high a likelihood to stable loan rates, and that when short-term trends become even more unstable or unpredictable, bankers respond by increasing their likelihood assessments of loan rate stability.

Slope scores for assignments of "higher" trends are strongly positive for bankers, indicating especially good "resolution skills" for this particular outcome. Bankers are particularly good at distinguishing information that indicates whether an upward trend will or will not occur in both periods. Slope scores were highly unstable across the two periods for "stable." Indeed, by the second period bankers were assigning higher probabilities to stable outcomes when they did not occur (0.63) than when they did in fact occur (0.52). Slope scores for "lower" improved in the second quarter.

"Bias" and "slope" (a.k.a. resolution) indicate two different qualities in a forecaster. Yates suggests resolution is the more valuable of the two. An interesting result is that different forecast qualities do not always rise and fall together over time. For example,

bankers' ability to issue probabilities to "lower" real estate rates become more biased and yet improved in resolution. Their ability to assign probabilities to "stable" rates became more biased and are less well resolved; "higher" is unchanged with respect to bias and less well resolved.

Summary and Conclusions

Agricultural bankers' ability to assign probabilities to quarterly trends in real-estate loan rates diminished considerably when subjected to a new monetary regime. This suggests that one unintended consequence of a major change in Federal Reserve monetary policy is a reduction in the ability of bank portfolio managers to make loan and other portfolio decisions based on their predictions of short-term movements in interest rates.

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Table 1. $\overline{PS}$

	Forecaster		
	Bankers	**Uniform**	**Rel Freq**
	1974:Q1 - 1979:Q3		
Lower	0.0450	0.1237	0.0416
Stable	0.1971	0.3011	0.2457
Higher	0.1758	0.2419	0.2382
Total	0.4179	0.6667	0.5255
	1979:Q4 - 1985:Q3		
Lower	0.2767	0.2506	0.2431
Stable	0.3739	0.2081	0.2066
Higher	0.2149	0.2081	0.2066
Total	0.8655	0.6667	0.6563

Table 2. Bankers' Bias Scores

	Lower	**Stable**	**Higher**
	1974:Q1-1979:Q3		
$\bar{f}$	0.03	0.67	0.30
$\bar{d}$	0.04	0.57	0.39
Bias	-0.01	0.10	-0.09
	1979:Q4-1985:Q3		
	Lower	**Stable**	**Higher**
$\bar{f}$	0.20	0.59	0.21
$\bar{d}$	0.42	0.29	0.29
Bias	-0.22	0.30	-0.08

Table 3. Bankers' Slope Scores

	1974:Q1-1979:Q3		
	Lower	**Stable**	**Higher**
$\bar{f}_1$	0.01	0.77	0.48
$\bar{f}_0$	0.03	0.53	0.18
Slope	-0.02	0.24	0.30
	1979:Q4 - 1985:Q3		
	Lower	**Stable**	**Higher**
$\bar{f}_1$	0.25	0.52	0.31
$\bar{f}_0$	0.16	0.63	0.17
Slope	0.09	-0.11	0.14

Table 4. Outcome Variance Measures

	1974:Q1-1979:Q3
Lower	0.0384
Stable	0.2451
Higher	0.2379
	1979:Q4 - 1985:Q3
Lower	0.2436
Stable	0.2059
Higher	0.2059

CONTINUOUS NUMERICAL CONTINUATION

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1. Introduction

Ordinary differential equations (ODEs) are widely used in physics, engineering, and many other technical specialties as tools for modeling and prediction. They are less well known in economics and business forecasting. An ODE is an equation which contains one or more derivatives, or *rates of change*. "Ordinary" means there is only one independent variable, often the *time*. The dependent variables might be things like the position of an artificial satellite or the values in an econometric time series.

Using ODEs requires some facility with the calculus and, in fact, is one of its more important applications. One of the most basic ODEs is

$$dx/dt = ax \tag{1}$$

whose solution is the exponential function

$$x = \exp at \tag{2}$$

Multiply $\exp at$ by any constant value and that also is a solution of (1). Practical applications require initial conditions, which means the value of x at some reference (or starting) time, say t_0. With initial condition x_0, the specific solution of (1) is

$$x = x_0 \exp a(t - t_0) \tag{3}$$

The guiding principle is that where you wind up depends on where you start, whether the phenomenon described is a satellite orbit or the price of gold.

ODEs can grow very rapidly in complexity just by adding more dependent variables, making **x** a vector. Mathematical purists would say that one is modeling a collection of variables with a vector, which is an element of a vector space. However, a collection of variables need not be elements of a vector space, but the vector notation is still used. To the modeler, a vector is a just a column of numbers whose vector operations (addition and scalar multiplication) may or may not be useful or meaningful.

The equation

$$\mathbf{dx}/dt = \mathbf{Ax} \tag{4}$$

is a system of linear ODEs with constant coefficients (the matrix **A**). In principle it can be solved by converting **A** to its Jordan canonical form, thereby separating the system into linear ODEs with one and only one variable. These can be solved with elementary calculus.

Systems of ODEs that are nonlinear usually cannot be separated. And nonlinear ODEs with a single dependent variable cannot always be solved using the more familiar functions of mathematics. There is a vast, arcane literature of special functions used to solve nonlinear ODEs and a smaller, but even more exotic literature on separable nonlinear systems.

There also is a considerable literature on perturbation theory, which may allow ODE systems similar to one of the rare solvable cases to be solved approximately. These methods were the key to success of classical celestial mechanics until recent decades. Most applications of systems of nonlinear ODEs, however, rely on numerical solutions generated on computers. These methods date to the late 19th century, when they were first developed by astronomers computing the orbits of comets and other bodies with large orbital eccentricities.

2. Predictability and Forecasting

The orbits of the major planets can be predicted rather accurately for thousands of years into the

future and, what is mathematically equivalent, extended thousands of years into the past. Ancient observations, though not always very accurate, help astronomers study these orbits. This level of predictability became a paradigm for science and even led to the notion of determinism: Given the equations (ODEs) and the initial conditions, the future could be predicted perfectly and the past could be reconstructed. Unfortunately, this is not true.

One problem is that the ODEs may not be perfectly accurate. But even if they were, the general rule is that more precise predictions require more precise initial conditions. For linear systems like (4), the error ellipse (or higher dimensional quadratic) for the errors in the initial conditions maps into another ellipse (or ellipsoid) with an exponentially growing largest axis.

Nonlinear systems are much worse. The error ellipse evolves into ever more complex figures that eventually resemble a fractal and would become one, supposedly, were it extrapolated for infinite time. The fractals in the coffeetable books of computer graphics are created using difference equations (the discrete time cousins of ODEs) that produce fractal aggregates in just a few steps. These remarkable fractal generators usually involve simple difference equations using complex rather than real dependent variables.

Some ODE solutions, of course, spiral into a stable equilibrium. Think about a chemical reaction (these are often modeled with ODEs). Rocks have been around for hundreds of millions or even billions of years, but at one time they were different substances or different mixtures.

3. System Dynamics

ODEs and difference equations were applied to economics, forecasting, population dynamics, and the social sciences in a limited way before the advent of the computer. A good biography and lucid expositions can be found in a text by Luenberger [1979]. These provided insight, but not much in the way of forecasting.

The first major attempt at applying large ODE systems for modeling and forecasting business, economic, social, and ecological systems was the System Dynamics school, founded by Jay Forrester, who became famous in his day for inventing the magnetic memory that made the first large-scale mainframe computers possible. He is enshrined in the Hall of Inventors at the Patent Office.

System Dynamics gained wide recognition with the publication of *Industrial Dynamics* [Forrester, 1961]. Interest peaked with the widely publicized "Limits to Growth" debate sponsored by the Club of Rome. But a survey by Wils [1988] found interest in the System Dynamics approach to be declining.

What happened? The System Dynamics modelers found that their computer programs were no better for forecasting than time series methods and usually worse. Their usual response was to make the model larger. They also would use low-precision methods of numerical integration, although the best available methods would not have been much good with thousands of dependent variables.

Having little success at forecasting, the System Dynamics school took to policy analysis. But since they admitted they could not forecast anything very well, their policy analysis was just as suspect as that of economists or lobbyists.

Knowledge of nonlinear dynamics spread to the broader technical community only after the publication of James Gleick's bestseller, *Chaos* [1987]. The subtitle proclaimed a "new science," even though the book traced its origins to the turn-of-the-century French mathematician, Henri Poincaré.

It is worth noting that Newton's equations of motion for the planets are nonlinear. Linear systems theory and linear ODEs did not become the workhorse of engineering until the physicist J. Willard Gibbs invented vectors in the 19th century.

It is often erroneously stated that the Newtonian *Weltanschauung* is linear and deterministic. Deterministic, yes, because chaos had not yet been identified in ODE solutions. But the theories of modern physics do not add nonlinearity, it was already there.

The problem of the pre-computer era was that Poincaré's publications were unintelligible to most technical people, and those of his few followers, the topological dynamicists, were even more so. A few astronomers, such as the late Victor Szebehely

[1967], published prolifically, but the System Dynamics school evidently did not search the astronomy literature. The contributions of Edward Lorenz, the meteorologist, and some other pioneers are now recognized outside the realm of their specialties.

Chaos is sometimes defined as "extreme sensitivity to initial conditions." This is inadequate, since linear systems can have this property; all that's needed is a single eigenvalue of **A** in (4) to have a positive real part. Chaos requires that the dynamic system map simple geometric aggregates into ever more complicated forms, such as fractals.

Traditional topological dynamics treats the mapping of aggregates (sets) by systems of ODEs. For applications it is better to think about the mapping of statistical distributions. One really starts with a multivariate normal distribution (for the errors of the initial conditions), not a solid ellipsoid. For a linear ODE system with constant coefficients (4), the normal distribution is preserved. For nonlinear systems it evolves into a mushy sponge.

Since chaos is common in ODE models with 3 or more variables, the bold approach of System Dynamics in adding lots of variables created models controlled mostly by numerical integration errors. It also is a fact that feedbacks are very difficult to identify and calibrate until their effects become quite pronounced.

Exponential growth is not sustainable, no matter what giddy technophiles choose to believe. When and how growth ends is impossible to predict. Good policies will lead to a "steady-state" economy; bad ones to collapse. Modeling and forecasting are useful tools for policy analysts, but they can never provide precise results or easy answers.

4. Creating ODE Models

Creating ODE models for disciplines whose theories are qualitative, such as economics, demographics, and every other discipline in which prediction is called "forecasting," is a special challenge. The basic principle is that the model should at least fit the data, even if it does poorly at forecasting.

The data series should be smoother than typical economic time series. Aggregation is one smoothing tool already widely used. Another is low-pass filters. Moving averages are popular, but the ramp filter [Morrison & Morrison, 1997] has definite advantages for forecasting. Any attempts at creating ODE models will want to use both.

Start with the simplest possible model, 2 or 3 variables at most. If you can't get a simple model to work, it is unlikely that making it larger will improve things. ODEs are inherently prone to instability. Those forces that produce some sort of stability in the real world may be difficult to identify.

Always identify the equilibrium points in your model. These are the cases for which

$$d\mathbf{x}/dt = \mathbf{0} \tag{5}$$

where your model is

$$d\mathbf{x}/dt = \mathbf{f}(\mathbf{x},t) \tag{6}$$

Compute the Liapunov exponents, which are just the eigenvalues of your model linearized at the equilibrium points [Luenberger, 1979, Morrison, 1991]. See if they make sense.

The creation of ODE models slightly more complex than the classical, solvable systems developed before the computer era is a challenge for economists and forecasters.

5. ODEs and Nonlinear Filtering

Time series forecasting is mostly the application of linear filtering to noisy data. By using a low-pass filter as a trend model and sometimes logarithms of the data, many nonstationary series also can be forecast with linear filtering [Morrison & Morrison, 1998].

Differencing the data tends to amplify high-frequency errors. Second or higher differences create the instability of polynomial extrapolations. First differences of logarithms of data are pretty much the practical limits for that approach and often work well for short data spans.

The dynamical interpretation of time series methods is noise-driven, damped linear systems. In other words, the model is

$$d\mathbf{x}/dt = \mathbf{A}\mathbf{x} + \mathbf{v}(t) \quad (7)$$

The components of $\mathbf{v}(t)$ are noise, in most cases the white noise model is used, and the real parts of *all* the eigenvalues of **A** are negative. The linear, homogeneous ODE acts as a low-pass filter on the noise $\mathbf{v}(t)$, producing $\mathbf{x}$, a *signal* that behaves like a detrended economic time series and various other phenomena. The time series approach is to work just with linear filters and forget about ODEs.

There are good reasons to suspect that the optimal damping model for undisturbed markets is nonlinear, just as is the case for most physical phenomena. Consumer purchasers are relatively insensitive to small changes in prices, but will reduce purchases or switch brands if prices increase too much or too rapidly. Professional purchasing agents, however, are more likely to be acutely price sensitive, especially for commodity products.

The model (7) features linear damping. This is much easier to visualize if one looks at a simple second-order equation rather than the general matrix form. Consider:

$$d^2x/dt^2 + a\, dx/dt + x = 0 \quad (8)$$

If $a = 0$, the solution is the harmonic oscillator (basically a sine wave). When $a > 0$, the term $a dx/dt$ acts as *damping*, with the result that x approaches 0 as t grows. As long as $a < 2$, the behavior remains oscillatory; but for $a \geq 2$, the oscillations disappear.

Eigenvalue analysis identifies the properties of the solution of linear systems such as (1), (4), and (8). It also identifies the parameter values of models of the type in (7) that are feasible. And the statistical properties of the solutions of (7), such as autocorrelation functions, can be determined using transfer functions and the rest of linear systems theory [Jordan, 1972; Morrison, 1991].

Even so, attempts to do this analytically can lead to techniques unfamiliar to most forecasters, such as special functions [Jordan, 1972]. The fast and easy route is Fourier transforms, which can be done economically with the FFT algorithm [Press *& al.*, 1986].

Nonlinear damping is often modeled in mechanical systems by a power of the velocity, such as $(dx/dt)^{3/2}$. In other words, the damping gets proportionally stronger with higher velocities. In markets, buyer resistance certainly grows stronger the farther one is from the equilibrium price or from the previous price. The question is whether this effect can be captured in a model using real data.

The model becomes

$$d\mathbf{x}/dt = \mathbf{f}(\mathbf{x},t) + \mathbf{v}(t) \quad (9)$$

Simulations can be constructed using nonlinear damping and then analyzed with the usual time series methods. A general principle is that all forecasting algorithms should be tested on simulations. Whether one algorithm performs better than another on real data may be purely a matter of chance. There have been many studies in which an *ad hoc* method does as well or better than one that is theoretically better [*e.g.*, Morrison and Douglas, 1984].

6. Numerical Solutions of ODEs

Numerical integration algorithms use interpolating polynomials to model solutions of ODEs approximately. Some, such as the Runge-Kutta methods, are single-step. Multi-step methods use more than one previous (vector) value of the solution. To improve precision, some, such as Romberg integration, use extrapolations of the results of what happens as the step size is decreased [Press, *& al.*, 1986].

The Romberg approach may be used, in some cases, to cope with singularities. Some investigators also have developed techniques that use functions other than polynomials, especially to cope with singularities [Morrison, 1976, 1980]. The concept might be extended from quadratures and cubatures to ODEs by using redundant variables.

One approach that is flexible and whose accuracy is limited only by computer floating-point precision is known as CAC (Continuous Analytic Continuation). The terminology is borrowed from complex function theory, but most applications have been for real values of the independent variable, usually the time.

The Taylor series (of one or more variables) is the model rather than an interpolating polynomial.

All one needs to do is evaluate higher and higher derivatives until the increasing powers of the time step $h < 1$ and the factorials in the denominators drive the truncation error below the limit of precision [Davis, 1962].

CAC is limited in application by the fact that fast, accurate computations of higher derivatives are possible only when they can be obtained from stable recurrence relations. Not all ODE systems can provide such relations. This is a situation akin to solvability: certain subtle mathematical symmetries must be present and they are not always there. The analyst is helpless when symmetries are lacking or insufficient.

7. Orthogonal Functions

The Taylor series is a critical analytic tool, but for approximating functions, other methods are better. One such is orthogonal polynomials. These have errors that are uniformly bounded within the range of approximation. Outside that range the errors soar. And such representations, with few exceptions, have no mathematical or physical meaning, whereas the Taylor (and Laurent) series are primary mathematical tools for studying functions of a complex variable.

The numerical advantage of orthogonal polynomials is that they *always* can be computed by stable recurrence formulas, and they are what are required, rather than higher derivatives of the "right-hand sides" of the ODEs. Coefficients of the expansions are obtained by quadratures (the simple single-variable integrals of calculus). These quadratures may be done either analytically or numerically, depending on the case in hand.

The orthogonal *functions* most familiar to forecasters are the sines and cosines. These are ideal for modeling perfectly repeating cycles, but these are rare in nature (and economics). Time series analysis, however, makes good use of discrete and continuous Fourier transforms.

Another set of orthogonal functions receiving attention these days is the wavelets. These functions are better suited for image processing and certain kinds of signal processing than the Fourier transforms that were used formerly. In general, however, economic and business forecasting are best accomplished with Fourier methods, since the nonstationarity is weak. Each application has its own optimal set of orthogonal functions.

The best set of orthogonal functions for representing functions that are not perfectly periodic is the Chebyshev polynomials (and also functions that are not sums of a few periodic functions, but with incommensurable periods). However, these polynomials are defined by using trigonometric functions as

$$T_n(t) = \cos(n \arccos t) \tag{10}$$

Note that we designate t as the independent variable, but it need not be time.

Obviously,

$$T_0(t) = 1 \tag{11.1}$$

$$T_1(t) = t \tag{11.2}$$

By induction it is easy to show that all the Chebyshev functions are indeed polynomials. The next two are

$$T_2(t) = 2t^2 - 1 \tag{11.3}$$

$$T_3(t) = 4t^3 - 3t \tag{11.4}$$

An unusual property of the Chebyshev polynomials is that they are not only orthogonal over the interval [-1, 1] with a weighting function $(1-t^2)^{-0.5}$ but also over certain discrete sets within that interval, but ones with a nonuniform distribution.

A good tutorial on Chebyshev polynomials and their suitability for representing functions is in *Numerical Recipes* [Press, *& al.*, 1986]. A useful reference is the famous *Handbook* compiled by Abramowitz and Stegun [1964]. This is a wheel that does not need reinventing, so we will concentrate on what needs to be done to adapt Chebyshev polynomials to solving ODEs numerically.

8. CNC — Continuous Numerical Continuation

The term CNC was chosen to be analogous to CAC. When analytic results can be attained, they often, but not always, are to be preferred to the results of some numerical calculation. Numerical solutions frequently must be used because the

symmetries that permit an analytic solution do not exist. The design motif for CNC was to be as precise as CAC, but applicable to a much wider range of ODEs.

Constructing the integral of a function already expressed as a linear combination of Chebyshev polynomials is easy. It is another such linear combination. The trouble created by nontrivial ODEs is that the functions (time derivatives of the solution) are not known. So an iterative process must be set up.

A first guess is made at the solution function, which is, in general, a vector function. This is fed into the "right-hand sides" of the ODE system to compute time derivatives. These are then integrated to obtain a second, hopefully better, approximation to the solution function. The process is repeated until some error tolerance level is reached or divergence is detected.

For rapid development Euler's method was chosen as a starting procedure. Being just a linear extrapolation, this starting method is highly inaccurate, but it did demonstrate that CNC converges even from a bad first attempt. The principal disadvantage of using Euler's method is that too many iterations are required to converge, so the algorithm is rendered too computationally intensive, and hence slow.

To reduce computation times, Gill's variation of the fourth-order Runge-Kutta method was implemented as a starting method [Romanelli, 1960]. The nonuniform spacing of the sampling points does not cause any problems for Gill's method, since it is being used as a starting method, not for the ultimate result, so it need not be optimized.

CNC is a single-step method, but the step sizes can be much longer than those used for conventional single-step or multi-step methods. In general, it can be used with a step size comparable with the *sampling length* of a multi-step method, which typically is 8-14 times the time step size. This is possible because CNC is not only variable order, but multiple order; moreover, it does not use higher differences which tend to amplify noise, most of which is truncation errors.

For CNC the Gill method is not just a starting method, but also a *predictor*, since it must be run for every time step. Fourth-order Runge-Kutta methods use a 3-step procedure, with a half time step as a bootstrap point for the first two, so the predictor is part of the whole scheme. CNC is only a *corrector* and could be used with most any predictor to get initial estimates for the minimal number of sampling points. Shifting to a larger number of sampling points, when necessary, is done quickly and easily with the Chebyshev approximation already constructed.

Not only can the order in CNC be variable, so can the sampling frequency, which, of course, must be larger than the maximum order. One of the secrets of making CNC practical is to restrict the selection of sampling frequencies, *e.g.*, to powers of 2. Since cosines must be computed to locate the sampling points, this can be done efficiently only by a table look-up process.

The size of the cosine table is minimal if the sampling frequencies are powers of 2. Personal computers now have huge memory resources, 64 megabytes is not unusual, but it would be much too slow to adjust sampling frequencies up or down by steps of one. Doubling the sampling frequency if convergence does not occur is comparable to the usual practice of halving the step size in numerical integrations. The frequencies implemented are 8, 16, 32, 64, and 128 points per time step, which seem suitable for the 80-bit floating-point arithmetic supported by Intel CPUs and clones.

Numerical tests have indicated that step size control is still needed for certain problems, such as highly eccentric orbits. Other ODEs also can have solutions whose properties vary along the solution. So logic was created to cut step size in half until it is reduced by a factor of $2^{20} = 1{,}048{,}576$. If CNC does not converge upon reducing the step size that much, the user should do a little analysis.

CNC has far more variable parameters than other solution methods for ODEs. This is a great advantage, but it could allow the control logic to become very complex and the calculations correspondingly slow, if every parameter were to be fully optimized. Besides, tests made to date indicate that precision is not strongly dependent upon perfect optimization. For most applications, a minimally complex control logic is fast and yields precise results.

Of course, there is no end of examples where some system of ODEs will defeat a minimal control logic. The advantage of CNC is that the user can modify the logic without having to be an expert in the arcane subject of numerical analysis. The orders, the sampling frequency, and the decay rates of the Chebyshev coefficients are easy to interpret and easy to control to reach a desired precision, as long as it is supported by the floating-point arithmetic system being used, whether it is hardware or extended-precision software.

The current CNC release implements variable step size and the Gill starting method. The first release supported only fixed step size and used Euler's method for starting [*Critical Factors*, 1996]. Future developments to be conducted at Turtle Hollow Associates will include increasing the number of tests against complex solvable systems and creating applications to modeling and forecasting. The control logic will be made more comprehensive only as required.

9. Test Results and Stability Questions

Extensive numerical tests have been made to date on only a few ODE systems, mostly the harmonic oscillator and the 3-dimensional two-body problem. For these simple cases analytic solutions can be obtained to the limit of machine precision. The harmonic oscillator is one of the few Liapunov stable ODE systems; the primary source of error in the Kepler problem is drift along the orbit.

When the error tolerance was set to the minimum feasible value, solutions to the harmonic oscillator locked onto a periodic function, but, not of course, to the exact solution, which cannot be expressed only in rational (floating-point) numbers. The errors, with respect to the most precise possible solution attainable on the computer, also were another periodic function.

Tests were run for two-body orbits with the parameters of the moon and several cases typical of artificial satellites. After 26 years of "real time" (about 338 revolutions) the Keplerian drift of the moon was only a few centimeters. The "best" results were obtained when the along-track drift dropped back to zero and went the other way. Similar results were obtained for satellite orbits 60 days long (about 960 revolutions).

Future tests will include comparisons with Vinti's dynamical problem [Vinti, 1959a, 1959b, 1961], if an accurate code for its solution can be located. Other tests against complex, solvable ODE systems will be made as time and resources permit.

An important task not yet begun is an analytic stability analysis of CNC. This is simple in principle, since CNC is a linear operator and all one has to do is compute its eigenvalues. Our numerical tests indicate that there probably is no eigenvalue with a positive real part in the range of orders and sampling frequencies used to date. However, numerical tests do not ***prove*** that, nor do they indicate whether instability might arise for higher orders or denser sampling frequencies.

Stability while doing simple quadratures is not much of an issue, unless the instability is gross. One step and you're done. But with ODE solutions, hundreds or even thousands of steps may be involved. Any instability in the solution algorithm will react strongly with truncation errors in the floating-point arithmetic and the usual Liapunov instability in the mathematically perfect solution.

Floating-point precisions greater than 80 bits are already available as a hardware feature in some of the older supercomputers. The most advanced research is going to require fast floating-point implementations of arbitrary precision. So it is important to do an analytic stability analysis of CNC (really, quadratures with Chebyshev polynomials). Perhaps some brilliant mathematician has already published the most general result in an obscure journal.

10. Conclusions

There is a future for ODEs in modeling and forecasting, beyond the few areas, such as celestial mechanics, where they can yield precise predictions. The first is models slightly more complex than the solvable classics, such as the Volterra predator-prey model [Davis, 1962; Luenberger, 1979; Morrison, 1991]. The second is simulations of noise-disturbed, damped oscillators, both linear and nonlinear.

For all ODE applications, the CNC method offers an easy and flexible way to attain the highest precision that a given computing system can offer. An additional benefit is that it is fairly easy for the user to tailor the control logic for step size, sam-

pling frequency, and order without being an expert in numerical analysis.

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Futures Research Methodology

Paper prepared for FFC/99
By Jerome C. Glenn
co-director of the Millennium Project

The primary purpose of futures research is to give coherence and direction to planning processes. Futures research distills a vast array of information from many academic disciplines about dynamics that have shaped the world and how those forces might change to create new opportunities, threats, and uncertainties. Systematic stock-taking of the past and assessment of the future possibilities provides a clearer understanding of the conditions of the world today, leading to more informed decisions.

The Millennium Project itself is a method for global futures research. It is a global participatory think tank of over 500 futurists, scholars, and policy makers in 60 countries, who assess the future of humanity, evaluate policies, and document the range of views on the issues and opportunities we face at the millennium. It connects informed, perceptive, and imaginative individuals and institutions around the world to collaborate on research, surveys, and interviews. In order to connect research to implementation, leaders are interviewed as part of the assessment and are encouraged to participate in other project activities. The Project is *not* a one-time study of the future, but provides an on-going *capacity* for a broad selection of humanity to think together.

Increasing democracy requires that the public understands global issues sufficiently to give the mandate for action to leaders. The Millennium Project helps create a context for an on-going discussion and public education for such mandates.

The Millennium Project also produced a "handbook" of *Futures Research Methodology* that brings together the most comprehensive set of futures research methods ever assembled in one volume. It provides an executive overview of each method's history, description, primary and alternative usages, strengths and weaknesses, use in combination with other methods, and speculation about future usage. These papers also contains appendixes with applications and sources for further information. Over half of these booklets were written by the inventor of the method or by a significant contributor to its evolution.

Futures Research Methodology distills a half-century of futurist learning. It will help both the advanced researcher and beginner to create a range of possible and desirable futures for their nation, corporation, profession and other fields of study.

WHY FUTURES METHODOLOGY?

The purpose of futures methodology is to systematically explore, create, and test both possible and desirable future visions. Future visions can help generate long-term policies, strategies, and plans, which help bring desired and likely future circumstances in closer alignment.

Asking people to cooperate in building a better tomorrow is not reasonable without a shared, multi-faceted, and compelling image of the future. How such images are created influences the quality of the future.

Positive visions, untested by futures analysis, can be destructive by leading people toward impossible goals or impossible schedules

If no general agreement exists about an organization's or nation's future direction, then how can one know what is useful or useless? To what end would one cooperate? be efficient? Although, the application of futures methods to generate future visions will not eliminate conflict or competition, a people can have a shared future vision of economic competition toward a common goal.

The increasing complexity and acceleration of change decreases the lead-time for decisions and makes previous expectations less reliable. Forecasting increases lead-time between potential events and current planning. Hence, the faster pace and complexity of change today increases the value of early warning, because it increases time-space for analysis to create more intelligent decisions.

Another reason to use a range of futures methods today is that the understanding of time is changing. In the Information Age, the perception of time is more open. Hence, the contemporary focus on forecasting to determine what is possible and desirable, which is a far more complex task, requires a range of methods.

Perhaps the most commonly understood reason for the use of futures methods is to help identify what you don't know, but need to know, to make more intelligent decisions.

WHAT IS FUTURE STUDIES AND RESEARCH?

To study the future is to study potential change - not simply fads, but what is likely to make a systemic or fundamental difference over the next 10 to 25 years or more. Studying the future is not simply economic projections or sociological analysis or technological forecasting, but a multi-disciplinary examination of change in all major areas of life to find the interacting dynamics that are creating the next age.

Methods of futures research do not produce completely accurate or complete descriptions of the future, but they do help show what is possible, illuminate policy choices, identify and evaluate alternative actions, and, at least to some degree, avoid pitfalls and grasp the opportunities of the future.

We have always known it is smart to think ahead. But futurists do this as a profession, on a larger scale, and have methods and a body of writings to think systematically through the possibilities of tomorrow. One day, futures research may become an organized body of assumptions and methods with a more formal academic tradition; in the meantime, it can be thought of as an art in that it is creative and/or as a craft in that it applies knowledge with skill.

But unlike other crafts and arts, futures research and studies utilizes information from all of the sciences. The empirical base of the "futures field of knowledge," writes reviewer Pentti Malaska, "is all sciences, whereas the empirical base of anyone science is only that science's domain. A value of futures research is not discovering new factual knowledge as the sciences, but producing perceptions and insights to that body of knowledge."

To study the future, futurists scan the media to keep abreast of what is new that could indicate fundamental or systemic change. They also keep track of key individuals who are reliable sources of information about change in specific areas, make change themselves, and often have new ideas and insight into the processes of change. Futurists also apply a number of methods to explore the viability of current trends and, perhaps more important, future developments that could deflect those trends.

Futures research should be judged by its ability to help decision-makers make policy now, rather than whether a forecast was right or wrong. Futurists can make a forecast that is intended to be proven wrong.

In summary, if we do not know the consequences of our choices, our freedom to choose is an illusion. Hence, no freedom exists without forecasting, as was well argued by Bertrand de Jouvenel in the *Art of Conjecture*.

The *Futures Research Methodology* contains also an annotated bibliography by Michael Marien drawn from his publication *Future Survey*. Reading these annotations will provide an excellent overview of future studies methodology and related issues.

WAYS OF ORGANIZING METHODS

Futurists distinguish normative forecasting from exploratory forecasting. Normative work is based on norms or values. Hence, normative forecasting addresses the question: what future do we want? Exploratory forecasting explores what is possible regardless of what is desirable. This general division of futures work into normative and exploratory can be misleading when applied to methodology. Many techniques can be used for both normative and exploratory forecasting. Some tend to be used more for one than the other. Futurists "tools" are often quite flexible and adaptable to specific purposes.

Normative uses of futures methods answer the questions: what is the desirable future; what do we want to become? Exploratory uses of futures methods answer the question: what are the possible futures - whether they are desirable or not?

No agreement exists on the proper way to organize futures methods, although enough experience has accumulated that this should be possible. In the meantime, the organization of futures methods is an area for further research, and one that the Millennium Project should pursue.

Techniques can also be used "for" or "with" the client. Futurists can do their work largely independent of those for whom the forecast is done. They can receive the requirements for a study and return the results. The other methodological tradition involves the client, community, nation, or for whomever the study is done. The assumption of such participatory approaches is that client involvement in their own future is essential for understanding and acting on the results of the study.

Concurrent interest is growing in the future, instantaneous and global communications, powerful new nondeterministic modeling techniques, sharing information, systematic questioning software, data bases, and knowledge visualization. Now futurists, scholars, and others around the word can interact globally and take a fresh look at future possibilities, policies, and methodologies in ways not previously possible.

The methods in this series could be classified as shown in the table below.

A Simple Taxonomy of Futures Research Methods

	BY TECHNIQUE:		BY PURPOSE	
Method:	**Quantitative**	**Qualitative**	**Normative**	**Exploratory**
Environmental Scanning	X	X	X	X
Cross Impact Analysis	X	X	X	X
Decision Modeling	X		X	
Delphi		X	X	X
Futures Wheel		X	X	X
Gaming and Simulation	X	X	X	X
Genius Forecasting, Vision, and		X	X	X
Morphological Analysis		X	X	
Participatory Methods		X	X	
Relevance Trees		X	X	
Scenarios	X	X	X	X
Statistical Modeling				X
Systems and Modeling	X			X
Structural Analysis		X		X
Technology Sequence Analysis		X	X	X
Time Series Forecasts	X			X
Trend Impact Analysis	X	X		X
Normative Forecasting	X	X	X	

M3 - COMPETITION

Michèle HIBON and Spyros MAKRIDAKIS
INSEAD. France

The aim of this study is to verify if the four major conclusions of the M-Competition can apply.

1. Statistically sophisticated or complex methods do not necessarily produce more accurate forecasts than simpler ones.
2. The rankings of the performance of the various methods vary according to the accuracy measure being used.
3. The accuracy of the combination of various methods outperforms, on average, the individual methods being combined and does well in comparison with other methods.
4. The performance of the various methods depends upon the length of the forecasting horizon.

This study has been done on the enlarged, new database of 3003 series and includes 24 methods (in particular Expert Systems and Neural Network)

The number of time series used is 3003 series selected on a quota basis:
- 6 different types of series : micro, industry, finance, demographic and other,
- 4 different time intervals between successive observations (yearly, quarterly, monthly and other)

The historical values of each series are
at least 14 observations for yearly data,
at least 16 observations for quarterly data,
at least 48 observations for monthly data,
at least 60 observations for other data,

The time horizon of forecasting is :
6 periods for yearly
8 periods for quarterly
18 periods for monthly
8 periods for other

THE 3003 SERIES

Time interval between successive observations	TYPES OF TIME SERIES DATA						
	Micro	Industry	Macro	Finance	Demo-graphic	Other	TOTAL
Yearly	146	102	83	58	245	11	645
Quarterly	204	83	336	76	57		756
Monthly	474	334	312	145	111	52	1428
Other	4			29		141	174
TOTAL	828	519	731	308	413	204	3003

THE FORECASTING METHODS

Methods	Competitors	Description
Naïve/Simple		
1. NAIVE 2	M. Hibon	Deseasonalized Naïve (Random Walk)
2. SINGLE	M. Hibon	Single Exponential Smoothing
Explicit Trend Modes		
3. HOLT	M. Hibon	Automatic Holt's Linear Exponential Smoothing (2 parameter model)
4. ROBUST-TREND	N. Meade	Non parametric version of Holt's linear model with median based estimate of trend
5. WINTER	M. Hibon	Holt-Winter's linear and seasonal exponential smoothing (2 or 3 parameter model)
6. DAMPEN	M. Hibon	Dampen Trend Exponential Smoothing
7. PP autocast	H. Levenbach	Damped Trend Exponential Smoothing
8. THETA-sm	V.Assimakopoulos	Successive smoothing plus a set of rules for dampening the trend
9. COMB S/H/D	M. Hibon	Combining 3 Methods : Single/Holt/ Dampen
Decomposition		
10. THETA	V.Assimakopoulos	Specific decomposition technique , projection and combination of the individual components
ARIMA/ARARMA Model		
11. BJ-automatic	M. Hibon	Box Jenkins methodology of "Business Forecast System"
12. AUTOBOX 1 13. AUTOBOX 2 14. AUTOBOX 3	D. Reilly	Robust ARIMA univariate Box-Jenkins with/without Intervention Detection
15. AAM 1 16. AAM 2	G. Melard, J. M. Pasteels	Automatic ARIMA modelling with/without intervention analysis
17. ARARMA	N. Meade	Automated Parzen's methodology with Auto regressive filter
Expert System		
18. ForecastPRO	R. Goodrich, E. Stellwagen	Selects from among several methods: Exponential Smoothing/Box Jenkins/Poisson and negative binomial models/Croston's Method/Simple Moving Average
19. SMARTFCs	C. Smart	Automatic Forecasting Expert System which conducts a forecasting tournament among 4 exponential smoothing and 2 moving average methods
20. RBF	M. Adya, S. Armstrong, F. Collopy, M. Kennedy	Rule-based forecasting: using 3 methods - random walk, linear regression and Holt's to estimate level and trend, involving corrections, simplification, automatic feature identification and recalibration
21. FLORES-PEARCE1 22. FLORES-PEARCE2	B.Flores, S. Pearce	Expert system that chooses among 4 methods based on the characteristics of the data
23. ForecastX	J. Galt	Runs tests for seasonality and outliers and selects from among several methods : Exponential Smoothing, Box-Jenkins and Croston's method
Neural Networks		
24. Automat ANN	K. Ord, S. Balkin	Automated Artificial Neural Networks for forecasting purposes

The accuracy measures to describe the results of the competition reported in this paper are :
- MAPE : Symetric Mean Absolute Percentage Error,
- RANK: Relative Ranking,
-MEDAPE : Median Absolute Percentage Error,
- RMSE : Root Mean Square Error.
We have calculated an overall average of the accuracy measures, but we also focus, on this paper, on a breakdown of these measures for each category and time interval between successive observations.
The figures 1 to 4 are the graphics of the average MAPE of yearly, quarterly, monthly and other series, which allow to compare the performance of the methods which give the best results.
The tables 1 to 10 show the methods which give the best results, as follow :
-Tables 1, 2, 3, 4 : comparison of the 4 accuracy measures, on each category, for each time interval.
-Tables 5, 6, 7, 8 : detailed results per category and per time interval for each accuracy measures.
-Table 9 : comparison of the results given by MAPE on monthly data per category for short, medium and long step horizons.
-Table 10 : comparison of the results over seasonal versus non-seasonal data.
The best way to understand the results is to consult the various tables carefully.

The different accuracy measures
Tables 1, 2, 3, 4 give the results for the four different accuracy measures which have been used. We can see that most of the time each accuracy measure identifies the same methods which give the best results for the different types of data.

Effects of the type of series
The table 5 shows for each category and each type of data, which methods are significantly better than others.
We found that THETA is performing very well for almost all types of data. Whereas other methods are more appropriate for a type/category of data :
ForecastPro for monthly data, for micro and industry data,
ForcX for yearly data, for industry and demographic data,
RBF for yearly data, for macro data,
Robust-Trend for yearly data and for macro data,
Autobox2 for yearly and other data,
AAM1/AAM2 for finance data,
COMB-SHD for quarterly data,
ARARMA for other data and macro data,
If we consider the series as seasonal versus non-seasonal data, in overall average, ForecastPro is significantly better than any other methods for seasonal data and THETA for non-seasonal data. In overall average, THETA and ForecastPro are significantly better than all the other methods.

Effects of forecasting horizons
The results which are displayed in the different tables are averages over the different step horizons i.e. 1 to 6 for yearly data, 1 to 8 for quarterly data, 1 to 18 for monthly data and 1 to 8 for other data. A question which might be of interest is what would be the results if we consider the averages over short, medium and long term horizons. The table 9 shows this result for monthly data assuming that :
short term = average 1 to 3
medium term = average 4 to 12
long term = average 13 to 18
We found that the methods THETA and ForecastPro which are doing the best as overall, are also doing well when we consider separately short, medium and long term.
For short term, in addition to THETA and ForecastPro, there are SMARTFcs, AutomatANN and ForcX.
For medium term, in addition to ForecastPro and THETA there is ForcX.
For long term, in addition to THETA and ForecastPro there is RBF which is always doing better (for any kind of data) for long term horizon than for short term.

The combining of forecasts
The COMB-SHD method is a simple combination of the forecasts given by the three exponential smoothing methods : Single, Holt-Winter's and Dampened Trend. It gives good results especially for quarterly data (for each category) and for industry data (for yearly and quarterly data).

Complexity of the methods
THETA which can be considered as a simple method gives the best results for almost each type of data.
Flores-Pearce methods and RBF are methods which are much time consuming and they didn't produce more accurate results ; and the neural-network method Automat ANN, didn't out-perform any other methods.

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Figure 1 - Average Symmetric MAPE : Yearly Data

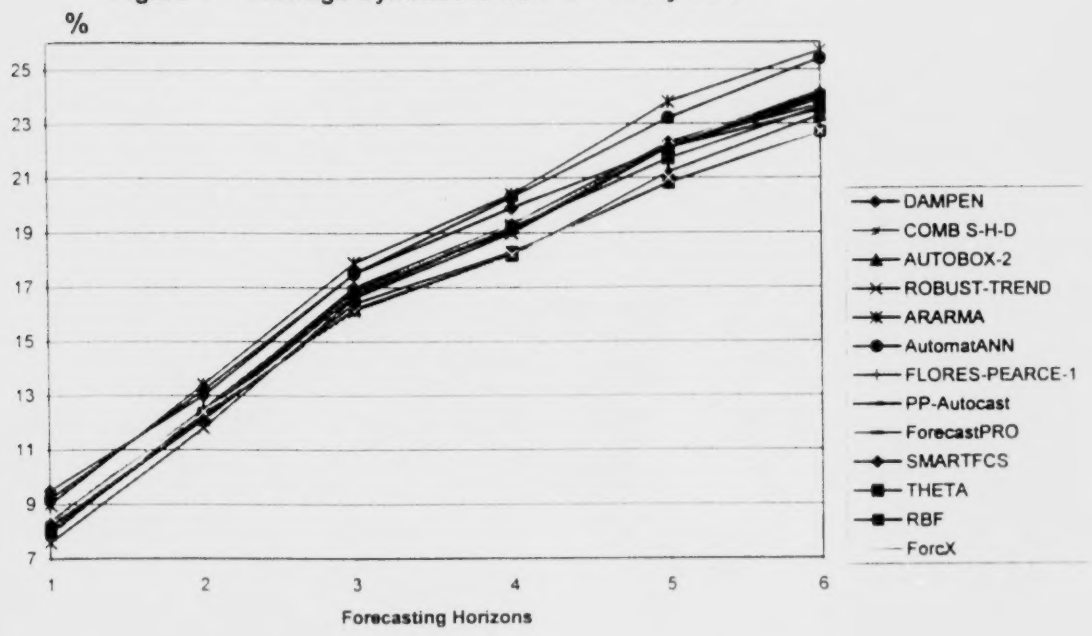

Figure 2 - Average Symmetric MAPE : Quarterly Data

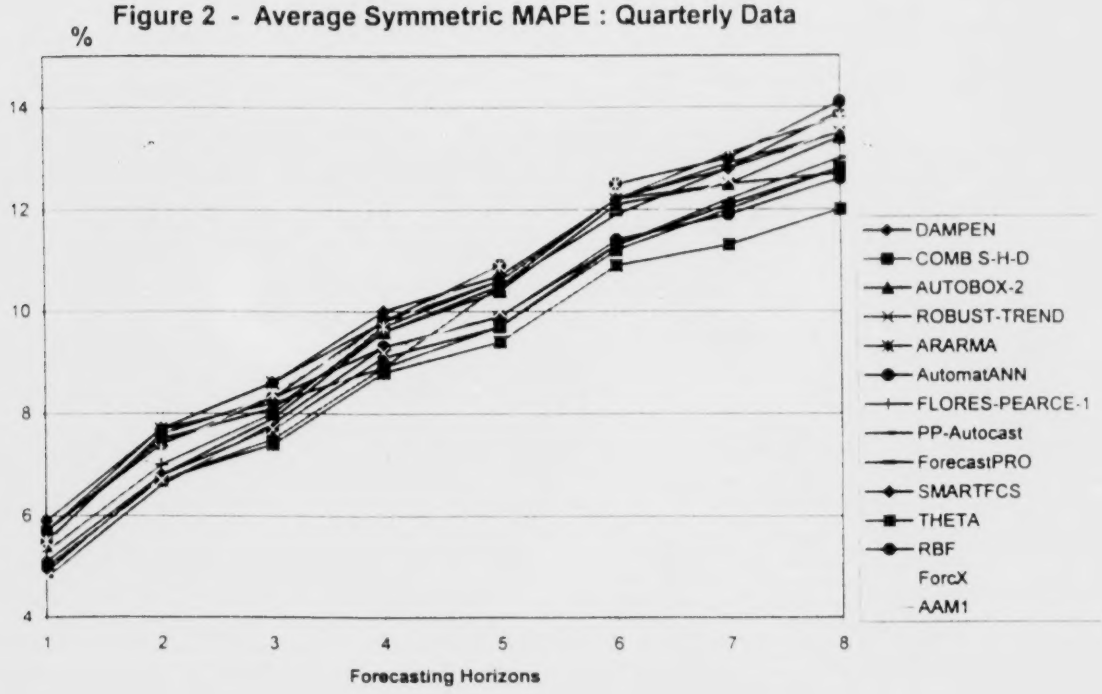

Figure 3 - Average Symmetric MAPE : Monthly Data

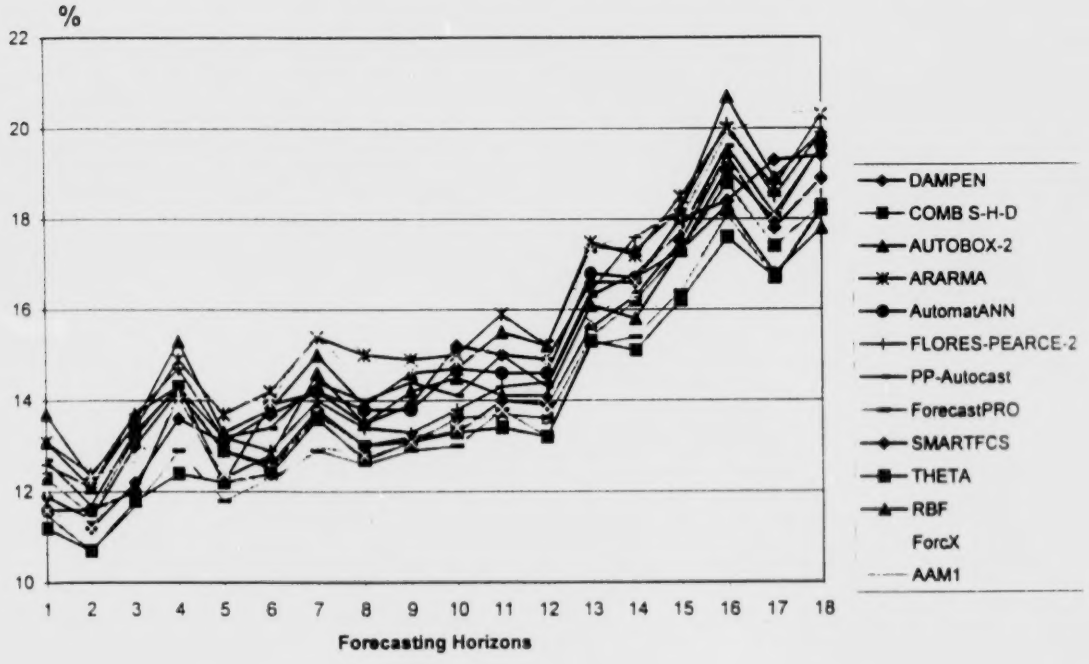

Figure 4 - Average Symmetric MAPE : Other Data

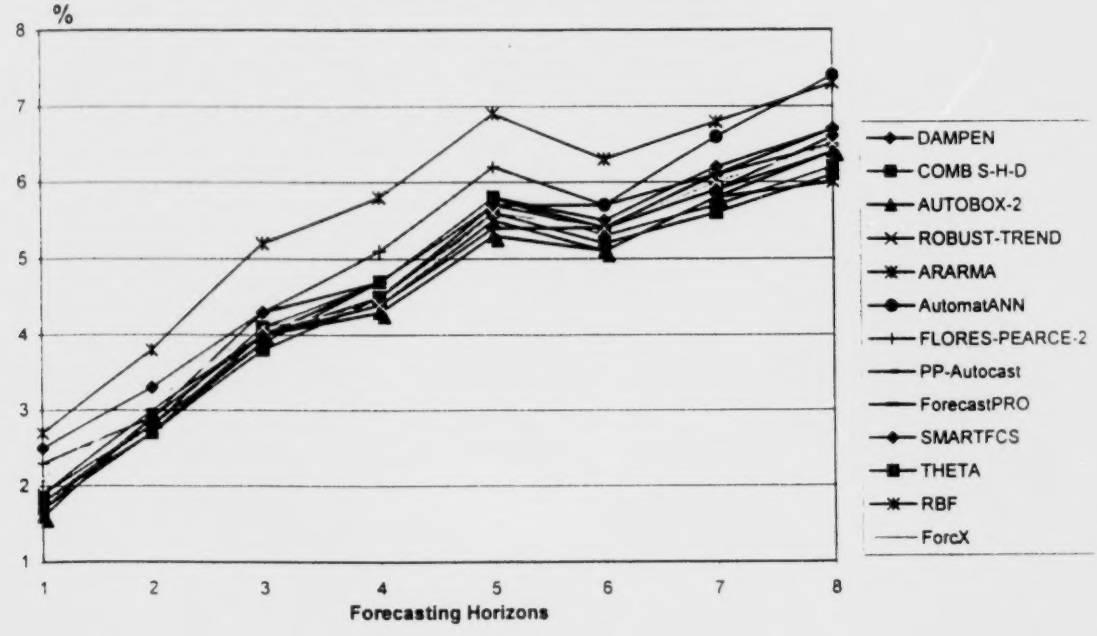

Table 1

Methods which give the best results : Yearly Data

Accuracy Measures	Micro (146)	Industry (102)	Macro (83)	Finance (58)	Demographic (245)	Total (645)
Symmetric MAPE	RobustTrend Flores-Pearc2 SMARTFcs Autobox2	THETA Comb-SHD Autobox2	RobustTrend ARARMA	Autobox2 SINGLE NAIVE2	ForcX RBF	RBF ForcX Autobox2 THETA RobustTrend
Average RANKING	RobustTrend THETA / Autobox2	THETA Comb-SHD / RobustTrend RBF	RobustTrend ARARMA RBF	SINGLE NAIVE2 / Autobox2 ForcX / ForecastPro	ForcX ForecastPro / PP-autocast	RBF / ForcX THETA / RobustTrend /Autobox2
Median APE	RobustTrend SMARTFcs	RobustTrend	RobustTrend ForecastPro	SINGLE NAIVE2 Autobox2	ForcX ForecastPro RBF THETA/ Autobox2	RBF FloresPearc1 PPautocast DAMPEN
RMSE	SINGLE NAIVE2 / RBF AutomatNN	RobustTrend THETA Comb-SHD	ARARMA RobustTrend Autobox3 / HOLT	RBF NAIVE2 SINGLE	THETA Comb-SHD ForecastPro	RBF RobustTrend SINGLE

Table 2

Methods which give the best results : Quarterly Data

Accuracy Measures	Micro (204)	Industry (83)	Macro (336)	Finance (76)	Demographic (57)	Total (756)
Symmetric MAPE	THETA Comb-SHD ForcX	Comb-SHD RBF ForcX PP-autocast	THETA Comb-SHD	THETA PP-autocast ForecastPro	THETA / SMARTFcs DAMPEN	THETA Comb-SHD DAMPEN PPautocast
Average RANKING	THETA HOLT Comb-SHD	Comb-SHD PP-autocast ForcX	THETA Comb-SHD DAMPEN	THETA ARARMA Comb-SHD	THETA / DAMPEN ARARMA	THETA Comb-SHD
Median APE	ForcX Comb-SHD HOLT	ForcX Comb-SHD THETA RobustTrend PP-autocast	THETA RBF FloresPearc1	THETA WINTER SMARTFcs	ARARMA RobustTrend	RobustTrend THETA Comb-SHD ForcX / DAMPEN PPautocast
RMSE	THETA ForcX Comb-SHD / PP-autocast	NAIVE2 / Comb-SHD SINGLE	THETA SINGLE	THETA PP-autocast ForecastPro	SMARTFcs THETA FloresPearc2 Comb-SHD	THETA Comb-SHD

Table 3

Methods which give the best results : Monthly Data

Accuracy Measures	Micro (474)	Industry (334)	Macro (312)	Finance (145)	Demographic (111)	Other (52)	Total (1428)
Symmetric MAPE	THETA ForecastPro	ForecastPro ForcX BJ-automat	ARARMA RBF	AAM1 AAM2	ForcX SMARTFcs SINGLE ForecastPro	Comb-SHD BJ-automat AAM1	THETA ForecastPro
Average RANKING	THETA ForecastPro	ForecastPro ForcX THETA BJ-automat Comb-SHD	RobustTrend HOLT WINTER ARARMA / AAM1	AAM1 AAM2	RobustTrend	THETA AAM1 / AAM2 ARARMA / Comb-SHD	THETA ForecastPro Comb-SHD
Median APE	THETA ForecastPro	ForecastPro BJ-automat ForcX THETA	RobustTrend HOLT AAM1	AAM1 / AAM2 Autobox3 Autobox1	RobustTrend ARARMA / RBF	ARARMA AAM2	ForecastPro THETA
RMSE	THETA ForecastPro Forcx	BJ-automat ForecastPro ForcX	THETA Comb-SHD ForecastPro / DAMPEN	AAM1 / AAM2 AutomANN ForcX	SMARTFcs ForcX / SINGLE	BJ-automat ForecastPro AAM1 / Autobox2	ForecastPro ForcX THETA

Table 4

Methods which give the best results : Other Data

Accuracy Measures	Micro	Industry	Macro	Finance (29)	Demographic	Other (141)	Total (174)
Symmetric MAPE						THETA Autobox2 Comb-SHD / RobustTrend ARARMA	ARARMA THETA / Autobox2
Average RANKING				PPautocast DAMPEN		ForcX / Autobox2 RobustTrend THETA	ForcX / Autobox2 THETA ForecastPro/ RobustTrend
Median APE				AutomANN		ForcX Autobox2	ForcX / Autobox2 THETA / ForecastPro/ RobustTrend
RMSE				DAMPEN PPautocast		Comb-SHD THETA	ARARMA

Table 5 **Methods which give the best results : Symmetric MAPE**

Time interval between Successive Obs.	TYPES OF TIME SERIES DATA						
	Micro (828)	**Industry** (519)	**Macro** (731)	**Finance** (308)	**Demographic** (413)	**Other** (204)	**TOTAL** (3003)
Yearly (645)	RobustTrend FloresPearc2 SMARTFcs Autobox2	THETA Comb-SHD Autobox2	RobustTrend ARARMA	Autobox2 SINGLE NAIVE2	ForcX RBF		RBF ForcX Autobox2 THETA RobustTrend
Quarterly (756)	THETA Comb-SHD ForcX	Comb-SHD RBF ForcX PP-autocast	THETA Comb-SHD	THETA PPautocast ForecastPro	THETA / SMARTFcs DAMPEN		THETA Comb-SHD DAMPEN PPautocast.
Monthly (1428)	THETA ForecastPro	ForecastPro ForcX	ARARMA RBF	AAM1 / AAM2	ForcX SMARTFcs SINGLE ForecastPro	Comb-SHD BJ-automat AAM1	THETA ForecastPro
Other (174)				DAMPEN / PPautocast AutomaANN ForecastPro		THETA Autobox2 RobustTrend Comb-SHD	ARARMA THETA / Autobox2
TOTAL (3003)	THETA ForecastPro	ForecastPro / ForcX THETA	RBF / ARARMA THETA / RobustTrend	AAM1 AAM2	ForcX		THETA ForecastPro

Table 6 **Methods which give the best results : Average RANKING**

Time interval between Successive Obs.	TYPES OF TIME SERIES DATA						
	Micro (828)	**Industry** (519)	**Macro** (731)	**Finance** (308)	**Demographic** (413)	**Other** (204)	**TOTAL** (3003)
Yearly (645)	RobustTrend Autobox2 THETA	THETA RobustTrend Comb-SHD RBF	RobustTrend ARARMA	SINGLE NAIVE2 / Autobox2 ForecastPro/ ForcX	ForcX PPautocast ForecastPro		RBF / ForcX THETA/ RobustTrend Autobox2
Quarterly (756)	THETA HOLT Comb-SHD	Comb-SHD PPautocast ForcX	THETA Comb-SHD DAMPEN	THETA ARARMA Comb-SHD	THETA / DAMPEN ARARMA		THETA Comb-SHD
Monthly (1428)	THETA ForecastPro	ForecastPro ForcX THETA Comb-SHD	RobustTrend HOLT WINTER ARARMA AAM1	AAM1 / AAM2	RobustTrend	THETA CombSHD ARARMA AAM1 / AAM2	THETA ForecastPro Comb-SHD
Other (174)				PPautocast DAMPEN		ForcX / Autobox2 RobustTrend THETA	Autobox2 ForcX THETA

Table 7 **Methods which give the best results : Median APE**

Time interval between Successive Obs.	TYPES OF TIME SERIES DATA						
	Micro (828)	**Industry** (519)	**Macro** (731)	**Finance** (308)	**Demographic** (413)	**Other** (204)	**TOTAL**
Yearly (645)	RobustTrend SMARTFcs	RobustTrend	RobustTrend ForecastPro	SINGLE NAIVE2 Autobox2	ForcX ForcastPRO RBF THETA Autobox2		RBF FloresPearc1 PP-autocast
Quarterly (756)	ForcX Comb-SHD HOLT	ForcX Comb-SHD THETA RobustTrend PPautocast	THETA RBF FloresPearc1	THETA WINTER SMARTFcs	ARARMA RobustTrend		RobustTrend THETA Comb-SHD ForcX
Monthly (1428)	THETA ForecastPro	ForecastPro BJ-automat ForcX THETA	RobustTrend HOLT AAM1	AAM1 / AAM2 Autobox3 Autobox1	RobustTrend ARARMA/ RBF	ARARMA AAM2	ForecastPro THETA HOLT Comb-SHD
Other (174)				AutomatANN		ForcX Autobox2	ForcX Autobox2 THETA ForecastPro

Table 8 **Methods which give the best results : RMSE**

Time interval between Successive Obs.	TYPES OF TIME SERIES DATA						
	Micro	Industry	Macro	**Finance**	**Demographic**	**Other**	**TOTAL**
Yearly (645)	SINGLE NAIVE2 / RBF AutomatANN	RobustTrend THETA Comb-SHD	ARARMA RobustTrend Autobox3 / HOLT	RBF NAIVE2 SINGLE	THETA Comb-SHD ForecastPro		RBF RobustTrend SINGLE
Quarterly (756)	THETA ForcX Comb-SHD PP-autocast	NAIVE2 / Comb-SHD SINGLE	THETA SINGLE	THETA PP-autocast ForecastPro	SMARTFcs THETA FloresPearce2 Comb-SHD		THETA Comb-SHD DAMPEN
Monthly (1428)	THETA ForecastPro ForcX	BJ-automat ForecastPro ForcX	THETA Comb-SHD ForecastPro DAMPEN	AAM1 / AAM2 AutomatANN ForcX	SmartFcs ForcX / SINGLE	BJ-automat ForecastPro AAM1 / Autobox2	ForecastPro ForcX THETA
Other (174)				DAMPEN PP-autocast		Comb-SHD THETA	ARARMA THETAsm Autobox2

Table 9

Methods which give the best results : Symmetric MAPE - Monthly Data

Average Step Horizons	TYPES OF TIME SERIES DATA						
	Micro (828)	**Industry** (519)	**Macro** (731)	**Finance** (308)	**Demographic** (413)	**Other** (204)	**TOTAL** (3003)
Short 1-3	SMARTFcs THETA ForecastPro AutomANN	ForecastPro ForcX DAMPEN Comb-SHD THETA	Most of the methods	Autobox2 / AutomANN ForcX	Most of the methods	Most of the methods	THETA ForecastPro SMARTFcs AutomANN ForcX
Medium 4-12	THETA ForecastPro	ForecastPro ForcX	Most of the methods	AAM1 / AAM2	Most of the methods	Comb-SHD BJ-automat	ForecastPro THETA ForcX
Long 13-18	THETA ForecastPro	THETA ForcX / RBF ForecastPro DAMPEN	RobustTrend RBF ARARMA AAM1	AAM1 / AAM2	SINGLE NAIVE2 / SMARTFcs ForcX / DAMPEN ForecastPro	AAM1 ARARMA RBF / Comb-SHD	THETA ForecastPro RBF
Overall 1-18	THETA	ForecastPro ForcX	ARARMA RBF	AAM1 / AAM2	ForcX SMARTFcs SINGLE ForecastPro	Comb-SHD BJ-automat AAM1	THETA ForecastPro

Table 10

Methods which give the best results : Seasonal / Non-seasonal Data

	TYPES OF TIME SERIES DATA						
	Micro (828)	**Industry** (519)	**Macro** (731)	**Finance** (308)	**Demographic** (413)	**Other** (204)	**TOTAL** (3003)
Seasonal (862)	ForecastPRO THETA DAMPEN Comb-SHD SMARTFcs ForcX			AAM1 / AAM2 ForecastPRO ForcX			ForecastPRO THETA / Forcx / DAMPEN Comb-SHD
Non-Seasonal (2141)	THETA			AAM1 / AAM2			THETA ForecastPRO ForcX / Comb-SHD

CONCLUSION

Comparison with the M-Competition

1. The performance of the various methods depends upon
   - the length of the forecasting horizon
   - the type (yearly, quarterly, monthly, others) of the data
   - the category (micro, industry, macro, finance, demographic, other) of the data

2. Accuracy measures are consistent in the M3 Competition

3. The combination of the 3 exponential smoothing methods does better than the individual methods being combined and very well in comparison with the other methods

4. Statistically sophisticated or complex methods do not necessarily produce more accurate forecasts than simpler ones

New methods

Some specific new methods not used in the M- Competition perform consistently better than the others in specific circumstances:

THETA, ForecastPRO for **Monthly data**
THETA for **Quarterly data**
RBF, ForcX, THETA, Robust-Trend, Autobox2 for **Yearly data**
Autobox2, ARARMA, THETA, ForcX for **Other Data**

THETA, ForecastPRO for **Micro data**
ForecastPRO, Forcx, THETA for **Industry data**
RBF, ARARMA, THETA, Robust-Trend for **Macro data**
AAM1, AAM2 for **Finance Data**
ForcX for **Demographic Data**

ForecastPRO for **Seasonal Data**
THETA for **Non-Seasonal Data**

The performance of the different methods do not significantly differ for **short, medium and long** term

Who has won the competition ?

It is not an appropriate question, and there is not a specific answer. It is more relevant to identify which methods are doing better than others for each specific type/category of data.

FORECASTING THE FOOD COMPONENT OF THE CONSUMER PRICE INDEX

Chair: Stephen A. MacDonald
Economic Research Service, U.S. Department of Agriculture

Discussant: David Richardson
Bureau of Labor Statistics, U.S. Department of Labor

Forecasting U.S. Retail Meat Prices When Consumer Tastes and Preferences Change,
Annette L. Clauson, Economic Research Service, U.S. Department of Agriculture

Forecasting Consumer Prices for Foods--A Demand Model Approach,
Kuo S. Huang, Economic Research Service, U.S. Department of Agriculture

Food CPIs: Forecasts from Vector Autoregression and Food Imports Prices,
Alberto Jerardo and Mark Gehlhar
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FORECASTING U.S. RETAIL MEAT PRICES WHEN CONSUMER TASTES AND PREFERENCES CHANGE

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Introduction

Along with energy prices, food prices are the most volatile consumer price category the government tracks. The only government entity that systematically examines food prices and provides food price forecasts (on an annual basis) is the Economic Research Service (ERS), an agency of the U.S. Department of Agriculture. Because of their uses in budgetary and public policy decisions, ERS' food forecasts receive much attention by other agencies and the media. There are several identifiable users of the ERS food forecasts, including the U.S. Federal Reserve Board, USDA Chief Economist and Secretary's Office, the U.S. Congress, other government agencies, the news media, the food retailing and processing industries, private consultants, companies, and universities. The food forecast estimates are used with other forecasts in the president's annual budget and are critical for determining the USDA's Food Stamp, school lunch, WIC, and other food program budget requests. Food service purchasing agents from hospitals, universities, state institutions, and military organizations also use ERS' food forecasts to support their budget requests and expenditures.

ERS currently uses historical indexes from the Bureau of Labor Statistics (BLS) Consumer Price Index (CPI) series to project price changes for the major food categories. The indexes that are forecast include All Food, Food Away From Home, Food at Home, Meats, Beef and Veal, Pork, Other Meats, Poultry, Fish and Seafood, Eggs, Dairy and Related Products, Fruits and Vegetables (Fresh Fruits, Fresh Vegetables, Processed Fruits and Vegetables), Sugar and Sweets, Cereals and Bakery Products, Nonalcoholic Beverages and Beverage Materials, and Other Food. The forecasts are short-term, usually for the next 12 to 18 months. In addition to short-term food price forecasts, USDA also projects long-term food price changes once a year as part of the U.S. Department of Agriculture's 10-year Baseline Projections. In this paper, the meat categories that will be analyzed include beef, pork, and poultry.

ERS has had the directive for forecasting food prices in some form since World War II. The inflationary period of the mid 1970's raised the importance of food forecasting by ERS analysts for USDA. As a result, it was recognized that price forecasts were increasingly affected by outside influences and analysts were required to consider an increasing amount of information. Behavioral econometric models, which account for changing economic conditions, were introduced for forecasting some of the major food categories such as beef, pork, poultry, eggs, and dairy products. ERS' model, the Quarterly Agriculture Forecasting Model (known in this paper as ERS Forecasting Model) used three-stage least squares to estimate consumer price indexes for the major components of the food at home CPI as well as an equation for food away from home.

Many of the traditional models used for forecasting retail food prices assume that past cycles, seasonality, and trends repeat themselves. But over time, consumers have made changes in their food preferences, such as consuming more poultry rather than beef or pork. If these changes are made by consumers and sustained over several years, how do traditional models measure-up when comparing forecasting models and methods? This paper will review the ERS Forecasting Model, which is a behavioral econometric model currently used to forecast beef, pork, and poultry retail prices, with an alternative univariate time series model and an inverse demand model approach. The models are compared from 1992 through 1998, which is after the last inflationary period ending in 1990 and during the time period when restaurants and fast-food establishments competed heavily with retail grocers for the consumer food dollar.

Insight into changing consumer tastes and preferences for beef, pork, and poultry can help explain the shifts in retail pricing of the competing meats. Consumer demand has affected market structure, with the impacts and successes of vertical coordination (especially for poultry and pork) resulting in changes in meat consumption. Per capita consumption and retail price changes for all meats in the past ten years (1989 to 1999) have indicated that:

(1) the poultry industry has maintained consistent increases in per capita consumption, from 57.2 to 96.0 pounds, while the deflated composite retail price has fallen 14 cents per pound; (2) the pork industry has maintained a steady level of per capita consumption, from 51.9 to 53.7 pounds, while the deflated composite retail price decreased 15 cents per pound; and (3) per capita beef consumption has decreased 9 percent from 69.3 to 63.4 pounds, with the deflated composite retail price down 44 cents per pound. Current demand models indicate that consumers should favor beef over pork or poultry, however, the changes in consumption patterns in the past 10 years have indicated otherwise.

Comparison of the Models

The three models compared for forecasting beef, pork, and poultry retail indexes in this paper are: (1) ERS Forecasting Model; (2) Time Series Model; and (3) Inverse Demand Model.

ERS Forecasting Model

The process for forecasting retail prices for beef, pork, and poultry at ERS begins with forecasting the farmgate price of the related raw commodities using a set of balance-sheet models that contain inventories, stocks of animals in the biological cycle, exports, imports, consumption, and farm, wholesale, and average retail prices. The analysts for beef, pork, and poultry forecast demand and supply factors (quantities, prices, income, and international trade) based on a combination of statistical analysis, rules of thumb, and conversations with industry experts.

The first margin, between farm and wholesale level prices, reflects demand and supply pressures at the processor wholesale level. The second margin reflects economic forces going from the processor wholesaler to the retail level. Both margins are allowed to change based on market information that the analysts have regarding the interaction among the prices for the three meats. On the retail side, when relative prices of substitutes like poultry and beef, seasonal demand factors, or per capita income growth are expected to change, the wholesale-retail margin is modified using established information. For example, retail per capita demand for pork is sensitive to real disposable income growth whenever it is expected to increase or decrease by more than 2 percent. Similarly, the wholesale-retail price-markups tend to vary according to seasonal factors, the competing prices of beef and poultry, inflation, and marketing specials. These rules can be described by the following function.

$$\textit{Retail Price} = \textit{Mark-up} * \textit{Wholesale Price}$$

where Mark-up = f(price of substitutes, specials, seasonality, input costs)

A model by Hahn (1989) is also used by ERS meat analysts to measure the importance of asymmetric feedbacks from the retail and farm prices to the wholesale price. In the results, the beef and pork model estimates implied that asymmetry is an important part of meat price transmission and in many cases the effects of asymmetry are large and statistically significant. The structural equation estimates for both beef and pork models implied that the wholesale level is the leading level. The models' estimates indicate that meat price transmission processes are complex: the pork model's estimates showed asymmetric feedback from the farm and retail levels to the wholesale level; while the beef results do not show asymmetric feedback.

Time Series Model

A time series model was developed as an alternative forecasting tool for ERS analysts. The estimates from this model were estimated using the same information available to ERS staff when their 1984 to 1998 forecasts were made. To obtain the optimum time series model, the ERS forecasts made from 1984 through 1991 were used to forecast 1992 through 1998. The menu based Time Series Forecasting System in SAS and various other procedures in SAS' Economic Time Series (ETS) were used to identify an alternative time series model that best fit the observations from 1984 through 1991, and then used to measure the time series model's forecast performance from 1992 through 1998.

The best alternative time series model was selected after performing the following procedures and steps: First, SAS' ETS procedure was used to perform a test of the log transformation, and if the log transformation could not be rejected, the logged data were analyzed. Next the procedure tested the statistical significance of seasonal dummies with an autoregressive model of large order. When the set of seasonal dummies could not be rejected, the models for analyzing beef, pork, or poultry contained seasonal dummies. Once the data were transformed, the model selected to compare with ERS' forecasts was the one with the smallest root-mean-squared error (RMSE) among the alternative univariate.

ARIMA, and seasonal models. The univariate model selected for forecasting beef was AR(3) with seasonal dummies; the model used for forecasting pork was MA(1) with seasonal dummies; and the best poultry model was MA(2) with two seasonal dummy variables.

The MA(1) model with seasonal dummies minimized the RMSE for pork and the MA(2) model with two seasonal dummy variables minimized the RMSE for poultry. Exponential smoothing models had similar fits to the MA(1) with seasonal dummies models; so the decision was made to use the moving average model. If y_t denotes the original time series, the MA(1) model is

$$y_t = \theta \epsilon_{t-1} + \sum_{k=1}^{k=4} d_k S_k + \epsilon_t$$

where ϵ_{t-1} is last quarter's forecast error,

ϵ_t is the current quarter's forecast error, S_k are

quarterly seasonal dummies defined in the usual way, and θ and the d_k are parameters to be estimated.

The AR(P) model with seasonal dummies minimized the RMSE criterion for the beef price data. This model is given by

$$y_t = \alpha_1 y_{t-1} + \ldots \alpha_p y_{t-p} + \sum_{k=4}^{k=1} d_k S_k + \epsilon_t$$

where the α =1 are parameters to be estimated.

Inverse Demand Model

An inverse demand model includes economic rationale in the meat price forecasts by applying an inverse demand system in which prices are functions of quantities and income. It includes the amount that consumers will buy at given prices and the prices at which consumers will buy given quantities. The inverse demand system expresses the function of quantity into price.

The inverse demand system recognizes that lags between farmers' decisions on production and commodities marketed may predetermine quantities available, with price adjustments providing the market-clearing mechanism. The economic rationale in this model is that it is capable of capturing the demand-pull factors of food utilization and income in the movement of meat prices.

The inverse demand model developed to formulate the price forecasts for beef, pork, and poultry in this paper is outlined and discussed in the presentation following this one. See *Forecasting Consumer Prices for Foods--A Demand Model Approach*, by Kuo S. Huang, Economic Research Service, U.S. Department of Agriculture. The data Kuo Huang presents in the following paper in Table 5 was projected back to 1992, using the same information. The quantities of beef, pork, and poultry were drawn directly from USDA's Baseline Projections, the growth rates of nonfood quantity and per capita income growth rate were assumed to be 1.22 and 4.14 percent respectively. In this paper, the results of food price indexes from 1992 to 1998, with a base of 1982-84=100 were simulated and used. These forecasts from the inverse demand model are then compared with the 1992 to 1998 forecasts from the ERS Forecasting Model and Time Series Model.

Results of the Models

From the statistical viewpoint, the model winner is obvious. The Time Series Model had the lowest RMSE for each of the meats (Table 1). Second, was the ERS Forecasting Model, and last place was the Inverse Demand Model. However, from a forecaster's perspective, the Time Series Model was not the clear winner.

For beef, the Time Series Model overestimated the actual index 4 out of 7 years; while the ERS Forecasting Model never overestimated the actual index, and the Inverse Demand Model overestimated the last 3 out of 7 years (Figure 1). Likewise, for pork, the Time Series Model overestimated the actual index 4 out of 7 years, the ERS Forecasting Model overestimated the actual index the last year of the 7 years analyzed, and the Inverse Demand Model overestimated the actual index the last 5 out of the 7 years examined (Figure 2). For poultry, the model outcomes were very different. The Time Series Model overestimated the actual index only 1 of the 7 years analyzed, the ERS Forecasting Model never overestimated the actual index, and the Inverse Demand Model overestimated the actual index 5 out of 7 years (Figure 3).

Consumer meat consumption patterns have changed as incomes increase; food preparation time at home decreases; and quality, consistency, and convenience of meats are valued (Figure 4). Consumption of poultry (specifically broilers) grew 11 percent from 1992 to 1998 and is expected to increase another 12

percent in 1999 and 2000. Although beef and pork consumption varied during the years analyzed, the overall consumption growth for both meats was flat from 1992 to 1998. Reviewing the deflated average retail price changes for meats (Figure 5), beef prices have clearly dropped from about $2.03 to less than $1.70 per pound in 1998; pork prices dropped slightly, from $1.41 to less than $1.40 per pounds; and deflated poultry prices were the same both years, averaging 62 cents per pound in 1992 and 1998.

If consumer tastes and preferences for meats have changed in the past 7 years, the Time Series Model would not likely detect the changes. A time series model is under a rigid assumption that the pattern in the past movement of a price variable can be used to predict future price movements. This model cannot provide any rationale of economic interpretation about the price movements, and would not be reliable in forecasting turning points. An inverse demand model would also have problems detecting changes in the relationship between quantity and price changes, if consumers alter their meat consumption patterns. And while the ERS Forecasting Model is a balance sheet of known inventories, animal stocks, exports, imports, consumption, and farm to wholesale prices, the forecasting of consumer purchases of meats at specific prices is less certain. As a forecaster, it is better to use a combination of models, realizing each of their strengths and weaknesses.

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Table 1. Model Forecasts for Beef, Pork, and Poultry, 1992 through 1998

	CPI Index	ERS Forecasting Model Index	Time Series Model Index	Inverse Demand Model Index
		BEEF		
1992	132.3	130.8	132.1	131.9
1993	137.1	133.7	136.9	135.6
1994	136.0	134.2	137.1	129.7
1995	134.9	134.1	134.9	133.7
1996	134.5	134.0	134.1	137.5
1997	136.8	136.3	137.3	143.2
1998	136.5	135.8	136.8	146.5
RMSE ANNUAL		1.3143	0.3857	4.1686
		PORK		
1992	127.8	125.3	129.0	127.8
1993	131.7	130.8	131.2	132.1
1994	133.9	133.0	135.1	127.9
1995	134.8	132.0	133.9	135.3
1996	148.2	143.2	145.9	151.3
1997	155.9	155.3	157.3	163.1
1998	148.4	148.5	151.3	151.6
RMSE ANNUAL		1.8286	1.4857	3.1700
		POULTRY		
1992	131.4	128.5	130.1	135.3
1993	137.0	133.0	134.1	138.2
1994	141.5	136.7	141.0	135.1
1995	143.5	140.5	142.2	144.3
1996	152.4	147.7	149.7	153.7
1997	156.7	155.0	157.1	166.2
1998	157.2	155.0	156.6	156.6
RMSE ANNUAL		3.3286	1.3857	4.3557

Figure 1

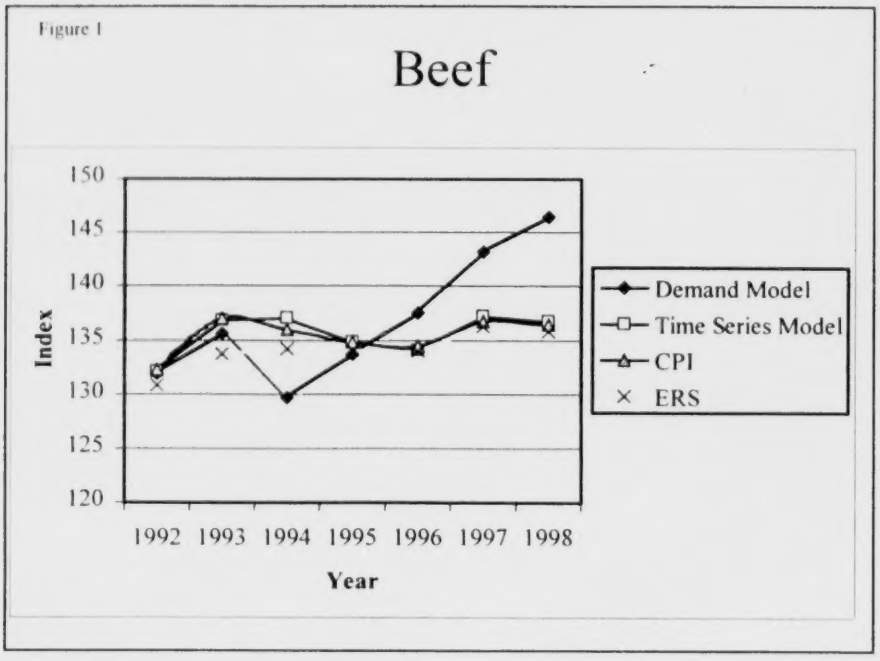

Figure 2

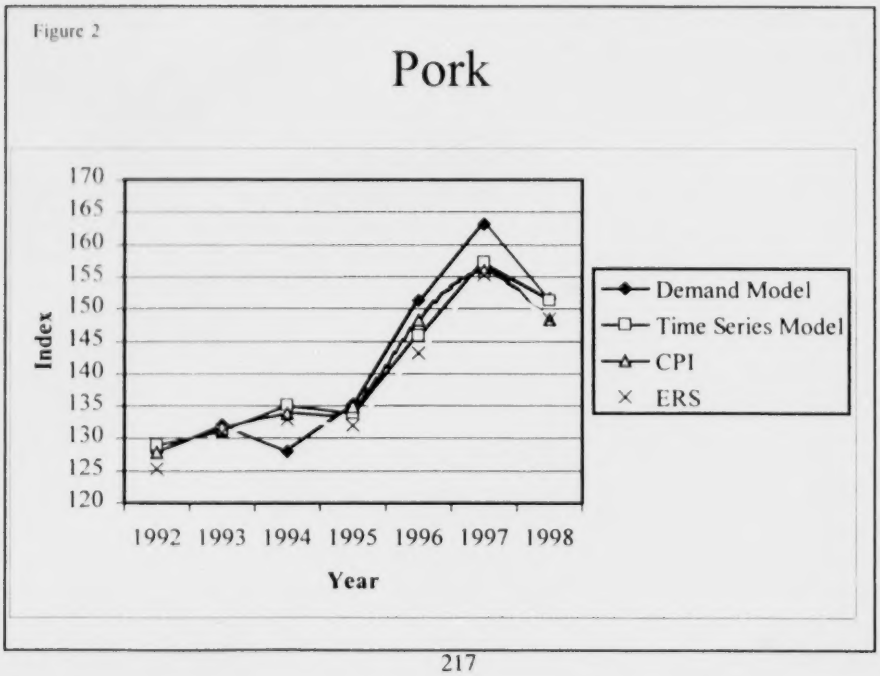

Figure 3

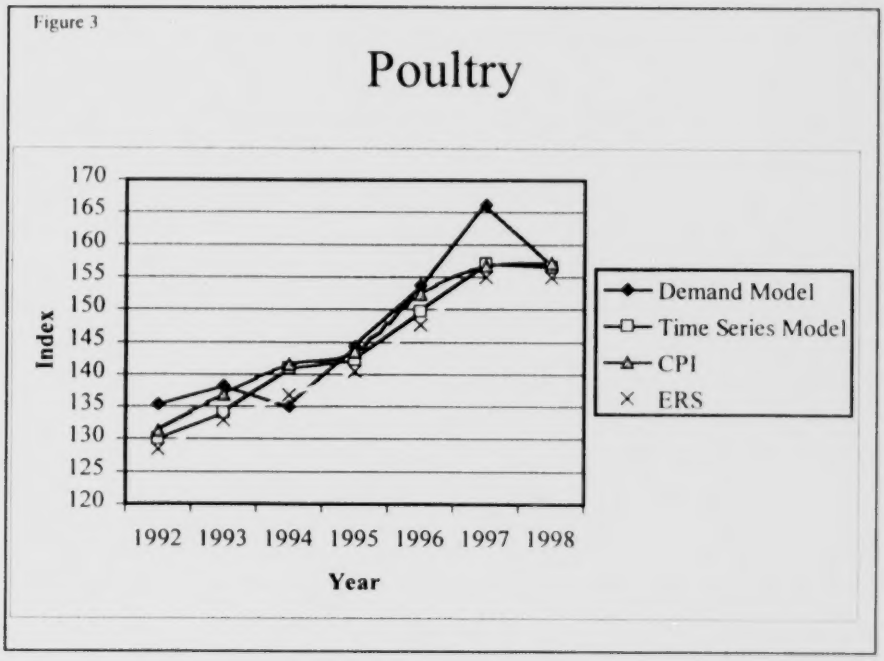

Figure 4

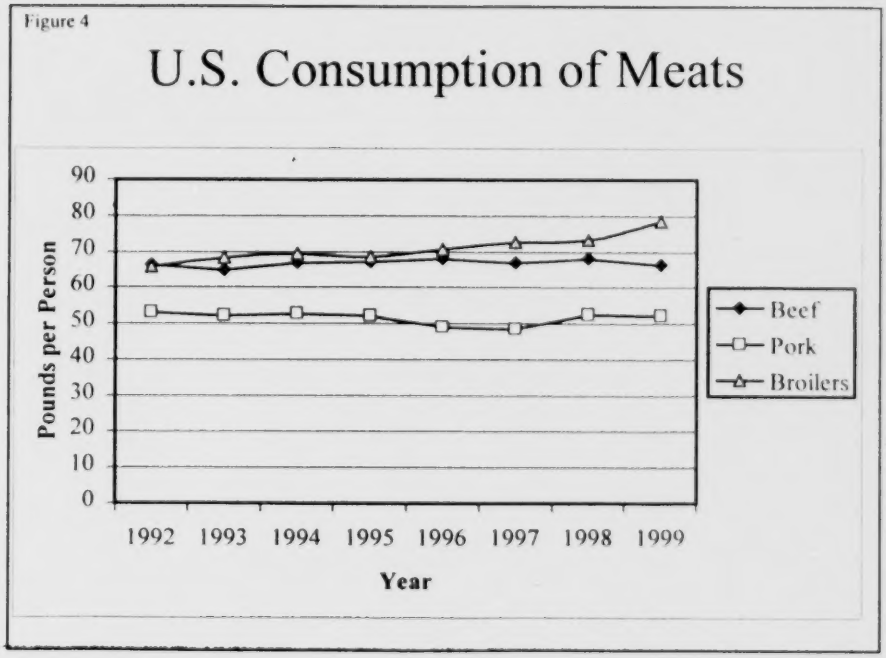

Figure 5

Deflated Retail Prices for Meats
250
200
150
100
50
0
Cents per Pound
1992
1993
1994
1995
1996
1997
1998
1999
Year
Beef
Pork
Broilers

Forecasting Consumer Prices for Foods--A Demand Model Approach

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Introduction

Forecasting food prices is an important component of USDA's short-term outlook and long-term baseline forecasting activities. A food price-forecasting model is needed to provide information for use by agricultural policy decisionmakers to evaluate the effects of changes in farm products due to farm programs, economic conditions or weather on food prices. The objective of this study is to develop a price-forecasting model that can be easily implemented for timely outlook and situation analyses.

Some food price-forecasting models use a time series approach such as ARIMA (autoregressive integrated moving-average) model in Box and Jenkins (1970). The time series model, which depicts the historical movement of time series data observations, is a convenient approach because of using mainly its own price variable to predict food prices. Because it does not incorporate any economic rationale, time series model may not provide reliable forecasts when there is a change in economic conditions.

To include economic reasoning in the food price forecasts, this study applies an inverse demand system, in which prices are functions of quantities and income. As indicated by Hicks (1956), the Marshallian demands have two functions: one shows the amounts consumers will take at given prices, and the other shows the prices at which consumers will buy at given quantities. The latter function, "quantity into price," is essentially what the inverse demand system expresses.

The inverse demand system is theoretically sound and has considerable appeal as applied to food price forecasting. It has been long recognized that lags between farmers' decisions on production and commodities marketed may predetermine quantities, with price adjustments providing the market-clearing mechanism. Therefore, quantities of food production and utilization are likely appropriate variables to use in food price forecasts. This price-forecasting model is capable of capturing the economic demand-pull factors such as food utilization and income in the food price movement.

A Price-Forecasting Model

In this section, a price-forecasting model is developed by applying an inverse demand system approach. Assuming that there are n goods in a demand system, let q denote an n-coordinate column vector of quantities demanded for a "representative" consumer, p an n-coordinate vector of the corresponding prices for the n goods, $m = p'q$ the consumer's expenditure, and $U(q)$ the utility function, which is assumed nondecreasing and quasi-concave in q. The primal function for maximizing consumer utility is the Lagrangian function:

(1) Maximize $L = U(q) - \lambda (p'q - m)$.

By differentiating the Lagrangian function, the necessary conditions for optimums are

(2) $u_i(q) = \lambda p_i \qquad i = 1, 2, .., n$

(3) $p'q = m$

in which $u_i(q)$ is the marginal utility of the ith good. In equation (2), λ is known as the marginal utility of income showing that the change in the maximized value of utility as income changes. This equation represents an equilibrium condition, in which each marginal utility divided by its price is equal (constant at λ) for all goods.

The inverse demand system can be obtained by eliminating the Lagrangian multiplier λ from the necessary conditions of equation (2). Multiplying both side of equation (2) by q_i and summing over n goods to satisfy the budget constraint of (3), the Lagrangian multiplier is then obtained as

(4) $\lambda = \Sigma_i q_i u_i(q) / m$

Substituting (4) into (2) yields the Hotelling-Wold identity, which defines the inverse demand system from a differentiable direct utility function as

(5) $p_i / m = u_i(q) / \Sigma_i q_i u_i(q) \qquad i = 1, 2, .., n$

in which p_i / m is the normalized price of the ith commodity. This equation represents an inverse

demand system in which the variation of price is a function of quantities demanded and is proportional to a change in income. For given quantities demanded, an increase in income will cause each commodity price to increase at the same rate. Therefore, all income flexibilities are implicitly constrained to one. This model has been applied in Huang (1991) for a 40-equation food demand system consisting of 39 food categories and 1 nonfood sector.

On the choice of functional form for equation (5), the loglinear approximation of the Hotelling-Wold identity is used in this study for practical reasons. The parameters of the loglinear form represent direct estimates of demand flexibilities. An annual statistical model for the ith price equation in terms of n quantities demanded is specified as follows:

$$(6)\quad \log\left(p_{it}/m_t\right) = \alpha_i + \Sigma_j \beta_{ij} \log\left(q_{jt}\right) + v_{it} \qquad i = 1, 2, .., n$$

where variables at time t are p_{it} (price of ith commodity), m_t (per capita income), q_{jt} (quantity demanded for jth commodity); v_{it}'s are random disturbances.

Furthermore, according to Houck (1966) and Huang (1994), the price flexibilities of β_{ij}'s should be constrained by the following theoretical relationships:

$$(7)\quad \beta_{ij} = (w_j / w_i)\,\beta_{ji} - w_j\,(\Sigma_k \beta_{jk} - \Sigma_k \beta_{ik}) \qquad i,j = 1, 2, .., n$$

where w_i is the expenditure share of ith food category.

As suggested by Muth (1961), there is little empirical interest in assuming that the disturbance term in a structural model is completely unpredictable, and it is desirable to assume that the part of disturbance may be predicted from past observations. Because the expected values of the disturbance could be related to economic conditions prevailing in the past years, the disturbance is assumed not independent over time but follows an autoregressive process.

Following Muth's suggestion, an autoregressive specification for the disturbance terms of the inverse demand system (6) is applied in this study to enhance the price-forecasting capability. An autoregressive process of residuals lagged up to k years is specified as follows:

$$(8)\quad v_{it} = \Sigma_k \gamma_{ik}\, v_{i\,t-k} + \varepsilon_{it} \qquad i = 1, 2, .., n$$

where ε_{it}'s are random disturbances in which ε_{it} is assumed to be identical normal and independently distributed as $\varepsilon_{it} \sim IN(0, \delta^2 I)$, and v_{it} is assumed to be serially correlated.

In the following empirical application, in addition to a structural component model of equation (6) is estimated, an autoregressive model by incorporating the disturbance specification of equation (8) are also estimated for testing if there is any improvement in forecasting performance.

Empirical Application

Data Sources

The model developed in the last section is used to formulate a price-forecasting model for the consumer prices of 16 food categories and 1 nonfood sector as defined in the structure of Consumer Price Indexes (CPI). These food categories are (1) beef and veal, (2) pork, (3) other meats, (4) poultry, (5) fish and seafood, (6) eggs, (7) dairy products, (8) fats and oils, (9) fresh fruits, (10) fresh vegetables, (11) processed fruits and vegetables, (12) sugar and sweets, (13) cereals and bakery products, (14) nonalcoholic beverages, (15) other prepared foods, and (16) food away from home.

To fit the model, price data is obtained from annual observation of the *Consumer Price Index* (USDL) from 1970 to 1996. The quantity data are compiled from *Food Consumption, Prices, and Expenditures* (Putnam and Allshouse, 1997). Most of food quantities are measured in retail weight. For example, the quantities of red meats are measured in retail cut equivalent. The quantity of poultry is measured in boneless trimmed equivalent. The quantities of dairy products are measured in milk equivalent on milkfat basis. Per capita income is calculated from total disposable income, obtained from *Personal Consumption Expenditures* (USDC), divided by the civilian population of 50 States at July 1 of each year. The quantity of nonfood sector is approximated as the per capita nonfood expenditures measured at constant prices; that is by dividing the current value of per capita

disposable income spent on nonfood with the consumer price index of all items less food.

Quantity data of some food categories can not be constructed to match the price indexes defined by the CPI. These categories are other meats, fish and seafood, fats and oils, processed fruits and vegetables, cereals and bakery products, other prepared foods, and food away from home. Hence the quantities of these categories are not used as explanatory variables in the model.

Some alternative proxy quantity data for these categories have been tried, but the estimation results are not satisfactory. For example, wheat food use was tried as a quantity proxy in the equation for cereals and bakery products but was not satisfactory. One reason is that wheat is only one farm-level ingredient in cereals and bakery products so the farm-level quantity is probably not representative to the retail quantity. Another reason is that the farm value represented by wheat quantity measure is a small share of the retail product value of cereals and bakery products.

For explaining price changes of those food categories with missing own quantity as an explanatory variable in the model, cross-quantity effects and per capita income are considered major determinants. For example, the price variations of other meat category are likely captured or represented by per capita income and the cross-quantity effects with beef, pork and poultry. Because some quantities are excluded from demand equations, the parametric constraints across demand equations (equation 7) can not be applied, and each price equation of the demand system is estimated separately.

Estimation Results

The estimation results by applying ordinary least squares are contained in table 1. The quantity variables of food categories, nonfood, and a constant term are listed across the top of the table, and the normalized price variables defined as the consumer prices deflated by the index of per capita income are listed down the left-hand side. For each pair of estimates, the upper part is the estimated price flexibility of a particular food category in response to the changes in quantities of its own category or other categories, and the lower part is the estimated standard error.

In table 1, the estimated price flexibilities in each column can be used to assess how a change in the quantity of a specific food category, while holding the quantities of other categories fixed, affects the changes of all food prices. According to the estimates of own-price flexibilities, a marginal 1-percent increase in the quantity of each food category would result in a decrease of its own price as follows: 1.36 percent for beef, 1.18 percent for pork, 2.25 percent for poultry, 1.37 percent for eggs, 1.29 percent for dairy, 2.11 percent for sugar, 0.99 percent for beverage, and 1.06 percent for nonfood. The estimated marginal price effects for fresh fruit and vegetable categories, however, are not statistically significant.

Regarding the cross-quantity effects, an estimated cross-price flexibility between two food categories shows the percentage change in the amount consumers are willing to pay for one food when the quantity of another food increases by 1 percent. A negative cross-price flexibility means substitution, while a positive sign signals complementary between the two goods. This is because a marginal increase of the quantity of one good may have a substitution effect on other goods, and the price of other goods should be lower to induce consumers to purchase the same quantity of the other goods. For similar reason, a positive cross-price flexibility means complementary relationship.

According to the estimates in table 1, for example, the cross-price flexibility of poultry with respect to the quantity change of beef is -1.15, and the cross-price flexibility of beef with respect to the quantity change of poultry is -0.77. The negative signs suggest beef and poultry are substitutes. Many of the estimated cross-price flexibilities, however, are not statistically significant. This is probably because even though some individual foods are either substitute or complement, aggregating process over different items mitigates these cross-quantity effects. Also, annual data aggregates over seasons may contribute to the lack of statistical significance in some estimated cross-price flexibilities.

The estimates of goodness of fit (R^2) in each price equation are satisfactory. Most estimates of R^2 are higher than 0.9. In particular, there are 11 out of 17 cases having R^2 higher than 0.97. Mo For explaining price changes of those food categories with missing own quantity as an

explanatory variable in the model, cross-quantity effects and per capita income are considered major determinants.reover, the Durbin-Watson (D.W.) statistics shown in the last column of the table suggest that the errors of each price equation are not serial correlated, and the estimated standard error is unbiased for use in significant test of estimated price flexibilities.

To clarify the forecasting results over the sample period, predictions on consumer price indexes are computed from the predicted normalized prices. To get a close look at the accuracy of recent price forecasts, a comparison of actual and predicted food prices over years 1994-96 is presented in table 2. The error of predicted price indexes over this period is within 5 percent in most cases.

In addition, the turning point errors over the sample period 1970-96 are listed at the last column of the table. Among 26 observed changes in the sample period for each price series, the number of turning point errors equal or less than 5 has 11 cases, between 6 and 10 has 5 cases, and only 1 case has 13 errors.

These forecasts suggest that the direction of simulated changes in price indexes is, in general, quite consistent with actual changes, and the inverse demand model with no correction for serially corrected disturbances can be used for price forecasts. Graphic comparisons of actual and predicted meat prices are presented in figure 1. This graphic presentation provides an additional information about forecasting performance.

To examine the possibility of improving forecasting performance, the residuals of the demand system are further specified as a second-order autoregressive process suggested in equation (8). The estimation results are presented in table 3, in which the entries under the columns of A(1) and A(2) are estimated coefficients of autoregressive residuals lagged by 1 and 2 years, respectively. For most of price equations, the estimates of R^2 show only a slight increase than those of estimated inverse demand model without an autoregressive specification for residuals (table 1). It appears that the application of an autoregressive model to this particular data set does not yield any significant improvement in forecasting performance.

Conclusion

A food price-forecasting model is developed to provide information about how changes in the quantities of food utilization affect consumer food prices. An inverse demand system, in which prices are functions of quantities and income, is applied so that quantities of food utilization can be used as instrumental or control variables in the food price forecasting. This model by incorporating economic rationale specification provides an alternative price-forecasting instrument to the time series model. The developed model is applied to 16 food categories and 1 nonfood sector, while food categories are classified consistent with those reported in the Consumer Price Indexes.

Regarding forecasting capability, the estimates of goodness of fit (R^2) in each price equation are satisfactory. Most estimates of R^2 are higher than 0.9, and there are 11 out of 17 cases having R^2 higher than 0.97. Also, in the simulation over the sample period, the number of turning point errors among 26 observed changes are less than 7 in most price series. These statistical results suggest that the estimated inverse demand model alone can be used for price forecasts. Since the forecasts of consumer food prices are conditional on the quantities of food utilization and per capita income, the major problem of applying this price-forecasting model, however, is the difficulty of obtaining a reliable prior information on quantities of food utilization and per capita income in the future.

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Table 1. Estimated price flexibilities--no autoregressive specification for residuals

Price\Qty	Beef	Pork	Poultry	Eggs	Dairy	Fruit	Veget.	Sugar	Bever.	N food	Constant	R**2	D.W.
Beef	-1.3605	-0.1528	-0.7674	1.1993	-1.2585	-0.2892	-0.3867	-0.1383	0.0928	0.1829	17.8605	0.99	1.92
	0.2130	0.1581	0.2752	0.5582	0.3409	0.3134	0.3980	0.3802	0.0883	0.2814	2.7094		
Pork	-0.6334	-1.1770	-0.8247	0.5703	-1.0164	0.1096	-0.4293	1.0090	0.2221	-0.3470	16.1976	0.99	2.14
	0.2109	0.1565	0.2724	0.5525	0.3374	0.3102	0.3939	0.3763	0.0874	0.2785	2.6816		
O.meat	-0.7710	-0.3403	-0.6768	0.7632	-1.1634	-0.0124	-0.6854	0.3891	0.0457	0.0382	15.7210	0.99	2.39
	0.2154	0.1599	0.2783	0.5644	0.3447	0.3169	0.4024	0.3844	0.0892	0.2845	2.7396		
Poultry	-1.1495	-0.2559	-2.2509	-0.0714	-0.8316	0.7686	-0.0510	1.9969	0.3127	-0.1165	12.2158	0.99	2.34
	0.1896	0.1407	0.2449	0.4967	0.3034	0.2789	0.3542	0.3383	0.0785	0.2504	2.4110		
Fish	-0.0374	-0.0558	-0.2019	0.9567	-1.0579	-0.1274	0.1529	-1.0536	-0.1710	0.7864	8.3512	0.92	1.80
	0.2119	0.1572	0.2737	0.5551	0.3390	0.3117	0.3958	0.3781	0.0878	0.2799	2.6945		
Eggs	-0.9707	-0.4338	-2.4334	-1.3650	-1.5139	0.4927	0.0020	3.4243	0.4137	-1.4949	22.4323	0.98	2.58
	0.4862	0.3608	0.6281	1.2740	0.7780	0.7153	0.9083	0.8677	0.2014	0.6422	6.1834		
Dairy	0.0308	-0.0093	-0.3478	0.2366	-1.2880	-0.0743	-0.0850	0.2734	0.0715	-0.6961	13.3030	0.99	2.58
	0.1377	0.1022	0.1779	0.3609	0.2204	0.2026	0.2573	0.2458	0.0571	0.1819	1.7517		
Fat-oil	0.0301	0.0570	-0.7367	0.4708	-1.5603	-0.2144	0.5264	-0.6883	-0.0217	0.1477	13.7804	0.97	1.71
	0.3441	0.2554	0.4445	0.9017	0.5507	0.5063	0.6429	0.6141	0.1426	0.4546	4.3764		
Fruit	-0.6099	-0.3547	0.1357	1.3392	-0.6518	-0.4650	0.3371	0.3262	-0.0444	0.0826	4.1767	0.79	2.03
	0.2224	0.1651	0.2873	0.5828	0.3559	0.3273	0.4155	0.3969	0.0922	0.2938	2.8288		
Veget.	-0.8031	-0.1618	-1.0896	-0.5347	-0.3288	0.1103	0.3124	1.6991	0.0124	-0.7964	11.8685	0.92	2.53
	0.2634	0.1955	0.3403	0.6903	0.4215	0.3876	0.4921	0.4701	0.1091	0.3480	3.3502		
Pro.F&V	0.1767	0.0333	-0.3282	0.2620	-1.0619	-0.3427	0.7545	-0.8652	0.0489	-0.2832	11.9946	0.99	2.34
	0.1625	0.1206	0.2099	0.4257	0.2600	0.2390	0.3035	0.2899	0.0673	0.2146	2.0663		
Sugar	0.3667	-0.0395	0.1152	0.0754	-1.9351	0.3251	0.0857	-2.1122	-0.2264	-0.0224	20.1405	0.91	1.49
	0.4300	0.3191	0.5554	1.1266	0.6880	0.6326	0.8032	0.7673	0.1781	0.5679	5.4679		
Cereal	-0.0616	-0.0956	-0.4200	-0.3883	-1.2404	0.3683	0.2718	0.3812	0.0706	-0.7619	13.2459	0.93	1.47
	0.2668	0.1980	0.3446	0.6991	0.4269	0.3925	0.4985	0.4761	0.1105	0.3524	3.3932		
Bever.	0.7514	0.4179	0.6092	1.2485	-0.5850	-0.3802	-1.6808	-3.0192	-0.9967	1.7639	13.2412	0.90	1.79
	0.5333	0.3957	0.6888	1.3972	0.8533	0.7845	0.9962	0.9516	0.2209	0.7044	6.7817		
Pro.food	0.2326	-0.0597	0.0379	0.1435	-0.9052	0.1764	0.0338	-0.1022	0.0657	-0.7563	9.8290	0.99	1.97
	0.1150	0.0854	0.1486	0.3014	0.1841	0.1692	0.2149	0.2053	0.0477	0.1520	1.4630		
F.away	0.0092	0.0275	-0.1209	0.1811	-0.2542	-0.0132	-0.1206	-0.3879	0.0409	-0.2762	8.8201	0.99	1.94
	0.0552	0.0410	0.0713	0.1447	0.0883	0.0812	0.1031	0.0985	0.0229	0.0729	0.7021		
N.food	0.0011	-0.0023	0.0347	-0.1107	0.0368	0.0060	-0.0403	0.1582	0.0199	-1.0647	9.0319	0.99	2.05
	0.0253	0.0188	0.0327	0.0663	0.0405	0.0372	0.0473	0.0452	0.0105	0.0334	0.3218		

Note: For each pair of estimates, the upper part is flexibility, and the lower part is standard error.

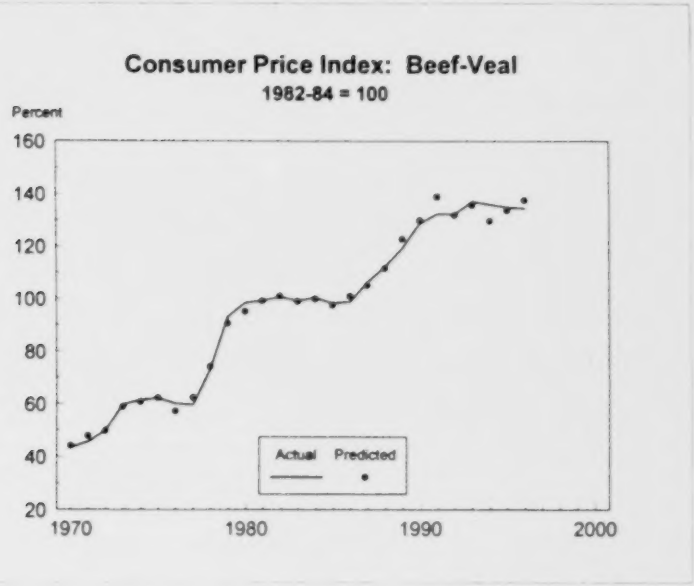
Table 2. Comparison of actual and predicted food price

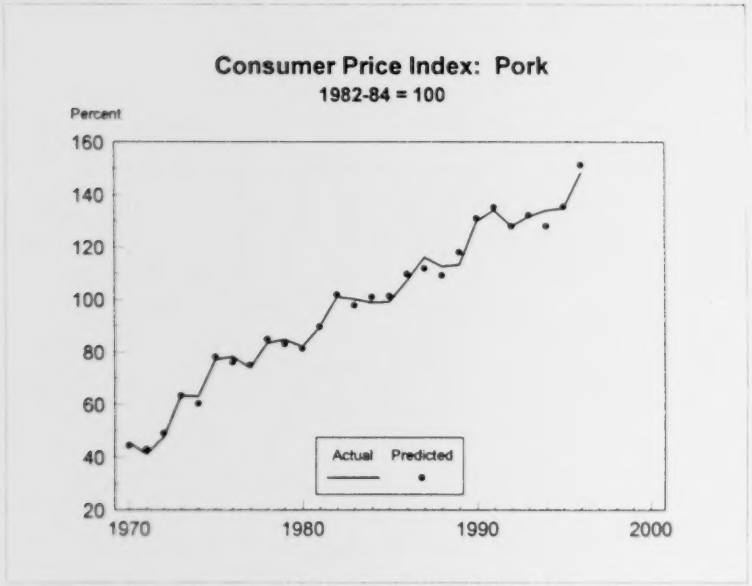
Comparison	Actual (1)			Predicted (2)			Error in percent [(2)-(1)]/(1)*100			Turning point errors
Years	1994	1995	1996	1994	1995	1996	1994	1995	1996	1970-96
Beef	136.0	134.9	134.5	129.7	133.7	137.5	-4.7	-0.9	2.3	3
Pork	133.9	134.8	148.2	127.9	135.3	151.3	-4.5	0.4	2.1	4
O.meat	137.0	139.0	144.0	132.4	138.8	145.3	-3.3	-0.2	0.9	6
Poultry	141.5	143.5	152.4	135.1	144.3	153.7	-4.5	0.6	0.9	8
Fish	163.7	171.6	173.1	163.1	168.6	178.6	-0.4	-1.7	3.2	2
Eggs	114.3	120.5	142.1	113.3	124.1	132.6	-0.8	3.0	-6.7	13
Dairy	131.7	132.8	142.1	129.9	134.8	140.5	-1.4	1.5	-1.1	2
Fat-oil	133.5	137.3	140.5	129.5	134.0	140.8	-3.0	-2.4	0.2	7
Fruit	201.2	219.0	234.4	205.5	213.0	231.3	2.1	-2.7	-1.3	2
Veget.	172.3	193.1	189.2	173.6	184.8	194.0	0.8	-4.3	2.6	4
Pro.F&V	134.5	137.5	144.4	133.5	136.7	143.3	-0.8	-0.6	-0.8	3
Sugar	135.2	137.5	143.7	132.0	133.5	141.6	-2.4	-2.9	-1.5	7
Cereal	163.0	167.5	174.0	156.8	162.7	174.3	-3.8	-2.8	0.2	1
Bever.	123.2	131.7	128.6	130.2	135.5	129.6	5.7	2.9	0.8	9
Pro.food	147.5	151.1	156.2	145.6	149.2	157.7	-1.3	-1.2	1.0	0
F.away	145.7	149.0	152.7	145.8	150.0	154.0	0.1	0.7	0.8	0
N.food	149.0	153.1	157.5	149.4	153.4	157.3	0.3	0.2	-0.1	0

Table 3. Estimated price flexibilities--autoregressive specification for residuals

Price\Qty	Beef	Pork	Poultry	Eggs	Dairy	F.fruit	F.veget.	Sugar	Bever.	N.food	A(1)	A(2)	Constant	R**2	D.W.
Beef	-0.8460	-0.2274	-0.3608	0.3967	-1.2647	-0.2092	-0.2775	0.2668	0.2390	-0.8022	-0.8205	0.7524	18.8205	0.99	1.82
	0.1817	0.1200	0.2239	0.5269	0.3469	0.2072	0.2629	0.3028	0.0754	0.4477	0.2078	0.1919	3.8204		
Pork	-0.2638	-1.0433	-0.6362	0.2524	-1.0465	-0.0646	-0.2800	1.1556	0.2511	-0.6267	-0.2582	0.7205	15.2035	0.99	2.26
	0.1478	0.1417	0.2164	0.4209	0.2736	0.2404	0.2724	0.2575	0.0619	0.2829	0.2255	0.1953	2.0574		
O.meat	-0.9558	-0.3115	-0.9195	0.7585	-1.3184	0.3551	-0.9719	0.4699	-0.0203	0.2481	0.7211	0.4732	16.8888	0.99	2.15
	0.2159	0.1921	0.3367	0.6201	0.2569	0.4048	0.4247	0.3935	0.0682	0.1741	0.2803	0.2822	2.2876		
Poultry	-1.1496	-0.3157	-2.1851	0.3598	-1.0240	0.8693	0.0128	1.8129	0.3154	0.0180	0.2236	0.4757	10.5450	1.00	2.32
	0.1726	0.1847	0.2693	0.5042	0.2712	0.3111	0.3498	0.3035	0.0718	0.2175	0.2616	0.2669	1.9804		
Fish	-0.0344	0.0633	-0.3370	0.8057	-1.0759	-0.0523	0.1648	-1.0224	-0.1446	0.8728	-0.1043	0.3795	8.1207	0.93	2.08
	0.1960	0.1715	0.2736	0.5658	0.3895	0.3242	0.3856	0.3645	0.0901	0.3115	0.3133	0.3008	2.5711		
Eggs	-0.7396	-0.2894	-2.4197	-1.3372	-1.0453	-0.6644	1.2282	2.9545	0.1920	-1.7173	0.9373	0.7208	22.2516	0.99	1.36
	0.3815	0.3508	0.5774	1.1032	0.4044	0.7448	0.7873	0.6973	0.1217	0.2763	0.2189	0.1932	3.8848		
Dairy	-0.1065	0.0189	-0.5355	-0.0336	-1.2430	0.1721	-0.4143	0.4528	0.0701	-0.5999	0.8108	0.4194	14.8275	1.00	2.07
	0.1420	0.1073	0.2011	0.3711	0.1564	0.2388	0.2701	0.2413	0.0414	0.1020	0.2529	0.2797	1.4374		
Fat-oil	0.1483	-0.0289	-0.6502	0.1337	-1.0638	-0.7635	0.6196	-0.3228	-0.1180	-0.1406	-0.2019	0.7054	14.6862	0.98	1.99
	0.2288	0.2214	0.3237	0.6886	0.3867	0.3739	0.4086	0.4111	0.0943	0.4313	0.1890	0.2085	3.0688		
Fruit	-0.6592	-0.4392	0.1797	1.4306	-0.6984	-0.3770	0.1985	0.2692	-0.0124	0.1630	0.1907	0.7493	4.3605	0.89	1.90
	0.1437	0.1893	0.2723	0.4730	0.2314	0.2768	0.2871	0.2723	0.0611	0.1915	0.2261	0.1940	1.6790		
Veget.	-1.0631	-0.5575	-1.0795	0.1384	-0.2419	-0.2410	1.0604	1.4698	-0.1187	-1.0726	1.0402	0.6001	12.4579	0.96	2.41
	0.2107	0.1804	0.3141	0.6163	0.2197	0.4067	0.4498	0.3931	0.0685	0.1492	0.2345	0.2287	2.1937		
Pro.F&V	0.3217	0.1277	-0.3303	-0.1915	-0.9021	-0.4772	0.8107	-0.6386	0.0405	-0.5331	0.1258	0.5708	12.7612	0.99	2.34
	0.1452	0.1707	0.2239	0.4647	0.2233	0.2791	0.2634	0.2612	0.0568	0.2073	0.2198	0.2988	1.6240		
Sugar	0.6509	-0.1290	0.2546	-0.3725	-1.3249	-0.2763	0.2798	-1.6120	-0.3893	-0.5430	-0.4639	0.7483	20.5807	0.96	2.33
	0.2539	0.2013	0.3237	0.7462	0.4422	0.3644	0.4233	0.4406	0.1041	0.5530	0.1660	0.1790	4.0815		
Cereal	0.1871	-0.0415	-0.2301	-0.2800	-1.0707	0.0305	0.2607	0.4526	0.0127	-0.7061	-0.5791	0.7248	10.9783	0.97	1.51
	0.1825	0.1191	0.1983	0.5550	0.2813	0.2120	0.2597	0.3197	0.0666	0.4366	0.2014	0.2051	2.9813		
Bever.	0.2509	0.0867	-0.4648	0.4781	-0.2998	-0.1892	-0.0660	-0.1041	-0.6055	0.0773	-1.5137	0.6626	8.3478	0.96	1.74
	0.3478	0.1979	0.4684	0.9553	1.0706	0.3086	0.4725	0.9817	0.1283	0.7093	0.2299	0.2280	7.5867		
Pro.food	0.2534	-0.0854	0.0450	-0.0147	-0.6483	-0.1620	0.1131	0.0285	0.0166	-0.8247	-0.2240	0.8633	10.4942	1.00	1.96
	0.0600	0.0593	0.0871	0.1769	0.1057	0.1013	0.1100	0.1058	0.0252	0.1122	0.1515	0.1197	0.8204		
F.away	0.0702	0.0300	-0.0305	0.3285	-0.4183	0.0856	-0.2335	-0.4888	0.0742	-0.1531	0.9203	0.6446	7.9950	1.00	2.01
	0.0493	0.0447	0.0750	0.1459	0.0536	0.0965	0.1042	0.0924	0.0161	0.0371	0.2207	0.2178	0.5134		
N.food	-0.0144	-0.0221	0.0411	-0.1588	0.0987	-0.0155	-0.0692	0.1986	0.0260	-1.0981	0.6023	0.7245	9.2735	1.00	2.08
	0.0195	0.0217	0.0314	0.0602	0.0258	0.0387	0.0402	0.0363	0.0072	0.0185	0.2037	0.1856	0.2038		

Note: For each pair of estimates: the upper part is flexibility, and the lower part is standard error.





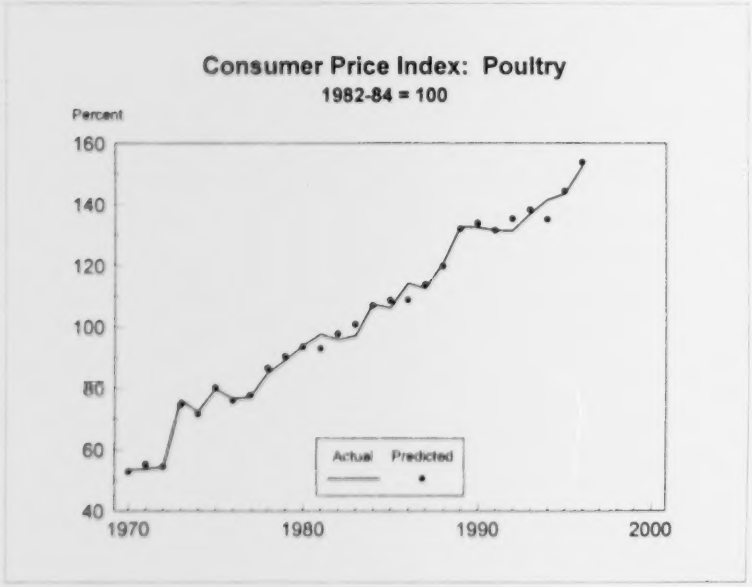


Figure 1: Graphic Comparison of Actual and Predicted Meat Prices

Food CPIs: Forecasts from Vector Autoregression and Food Import Prices

Alberto Jerardo and Mark Gehlhar, ERS/USDA

Introduction

The Economic Research Service (ERS) of USDA routinely forecasts components of the food consumer price indexes (CPI). These forecasts are used as inputs into policy-making by various agencies, including the Federal Reserve Board for monetary policy and for budget allocations for the Food Stamp Program. Another activity of ERS is providing both short and long-term projections of imports and exports of food and agricultural commodities. At present, trade and domestic price forecasting are conducted independently of each other. Food trade, however, is becoming increasingly important because of its impact on the domestic food market. The import share of a number of food items in food consumption of U.S. households has risen over the past decade and is expected to continue rising. International shocks such as lower commodity prices are transmitted to the domestic market in part via traded commodities. ERS forecasts of domestic food prices currently have no explicit treatment of the link between international and domestic prices.

This paper examines the extent to which food import prices have influenced food CPIs by estimating vector autoregression (VAR) models that include food import prices. Of importance here is how trade price indexes, including those based on exchange rates, can be used to forecast domestic food prices. Forecasts of the food CPIs are generated from dynamic projections of bivariate VAR models and exogenous projections of import prices.

Consumer Food Prices and Food Imports

In U.S. food trade, imports have a higher share of consumer-oriented food than exports, which have a large bulk-commodity share. The rise in import share of U.S. food consumption for a number of commodities in recent years (Putnam, pp. 136-8) suggests that imported food prices are more likely to affect prices of food consumed in U.S. homes. Thus, the CPIs for food categories which are more import-dependent, or have higher import content, would likely be more related to changes in imported food prices. For example, banana prices heavily affect fruit prices, coffee prices impact non-alcoholic beverage prices, and imported tomato prices affect domestic vegetable prices.

A related factor in the movement of U.S. food prices is the dollar's trade-weighted exchange rate. This variable is frequently used in trade forecasting. Since the dollar's exchange rate is its price in terms of another currency, a dollar appreciation effectively lowers import prices and thus also lowers domestic consumer prices. Given the rate of exchange-rate pass-through to food import prices, the dollar's appreciation (18 percent) in real terms since 1996 reinforces the general decline in international food prices since 1996. That is, the dollar's high exchange value puts downward pressure on domestic food prices by making imported goods less expensive and U.S. exports more expensive, thereby reducing input costs of domestic food processing. The net impact is an increase in supply to the domestic food market. Thus exchange rates can be used to help forecast domestic food CPIs.

The Food CPI Categories

The Bureau of Labor Statistics (BLS) estimates monthly consumer price indexes for various food categories that represent the average for all urban consumers in the U.S. From these, we selected the CPIs

of food categories which have corresponding import price indexes. The import shares among these food groups differ widely (16). The 10 food categories plus 2 beverage categories are the following:

1. Meats--beef, pork
2. Fish and seafood--fresh and processed
3. Dairy products--milk, cheese, and related products
4. Fats and oils--butter, margarine, salad and cooking oils, peanut butter
5. Fresh fruits
6. Fresh vegetables
7. Processed fruits and vegetables
8. Cereals and bakery products--flour, breakfast cereals, rice, pasta, cornmeal, bread
9. Sugar and sweets--including artificial sweeteners, candy, chewing gum
10. Other prepared foods--soups, snacks, condiments, sauces, baby food
11. Nonalcoholic beverages--coffee, tea, cocoa, fruit juices, carbonated drinks
12. Alcoholic beverages--malt beverages, wine, distilled spirits

The items included in each food category are in concordance with the BLS 1998 Revision. Among their import shares (in 1997) are 62 percent for fish and seafood, 34 percent for fresh fruits, 10 percent for fresh vegetables, 7 percent for red meats, and 1.9 percent for dairy products. The two food items for which ERS provides forecasts but were not selected here because of low import content are eggs and poultry.

Data Description

The CPI for each food category was taken from the BLS website (bls.gov). The monthly current series was not seasonally adjusted. The import price index (MPI) that most closely corresponds to the CPI was also downloaded from the BLS site. The MPIs were classified either under the Harmonized Commodity System (HS), the Standard International Trade Classification (SITC), or the End-Use Classification System. While the correspondence between the food CPI categories and their MPI counterparts is not exact, the items closely match.

In cases where food CPI categories have no matching import price index, exchange rate indexes were constructed as substitute import prices. The exchange rate index for each food category was constructed from real exchange rates that were weighted by corresponding U.S. import values from each foreign market. The pass-through percentage of exchange rate changes into import prices is assumed significant enough to indicate a matching direction of change in the short run. Otherwise, VAR estimation will reveal nonsignificant parameter estimators for the exchange rate index.

The dollar's real exchange rate vis-a-vis each country is computed for each food category as follows:

(exchange rate in foreign currency units per dollar) X (overall U.S. CPI / overall foreign CPI)

The exchange rate is corrected for relative price levels to account for relative purchasing power that may help determine the value of imports (income effect). The real exchange rate is weighted by the U.S. import value of the given food category from each country, then summed over all countries to obtain the exchange rate index (XRI). The weighted exchange rate import index represents the approximate price pattern over the sample period for each imported food group, assuming that importers face minimal price differentials due to world market competition. Thus, the exchange rate index for U.S. imports of dairy products (largely cheese and casein), for example, is a measure of the relative affordability of dairy products from all import-source countries. Over the sample time period, the exchange rate index would reflect the pattern of the

dollar's purchasing power. The nominal exchange rates and relative price levels used to compute the real exchange rates were obtained from quarterly forecasts by Oxford Economic Forecasting.

The Forecasting Model

A dynamic multivariate forecasting model was chosen in order to account for the autoregressive properties of monthly time series data (including trend, cycle, seasonality) as well as the lagged influence of theoretically related variables. Unlike univariate models whose out-of-sample forecasts are highly sensitive to outlying observations, a multivariate model can also include another variable or a dummy variable that accounts for the outliers. A vector autoregression (VAR) model possesses these attributes, which are critical for short-term time series forecasting. VARs are statistical, as opposed to econometric, models in that no simultaneous feedback is assumed, given only lagged, or predetermined variables as regressors. Thus the question of a variable's exogeneity does not arise in the econometric sense.

The dynamic relationship between food CPIs and their lagged values as well as feedback from lagged MPIs or XRIs can be best captured in a VAR model. VARs are transfer function models because the dynamic effects of other variables are added (or transferred) to the univariate lagged effects of the dependent variable. VARs are unrestricted in the sense that no prior assumption of dependence or independence is made between included variables, unlike simultaneous-equation or structural models. Nevertheless, VAR estimation results can be interpreted to reveal or confirm prior statistical causality between the variables.

The mathematical form of a general VAR model is specified as:

$$Y(t) = c + a(1)Y(t-1) + a(2)Y(t-2) + \ldots + a(p)Y(t-p) + Z(t) + e(t)$$

where Y(t) is a vector of endogenous variables, c is the constant or intercept, a(i) are the regression coefficients, p is the VAR order, Z(t) is a vector of exogenous variables, and e(t) is the white noise vector of disturbances.

Thus, for a p=2 VAR bivariate model with no exogenous variables:

$$y(t) = c(1) + a(1,1)y(t-1) + a(1,2)y(t-2) + a(1,3)x(t-1) + a(1,4)x(t-2) + e(1)$$

$$x(t) = c(2) + a(2,1)x(t-1) + a(2,2)x(t-2) + a(2,3)y(t-1) + a(2,4)y(t-2) + e(2)$$

where x(t) is the other endogenous variable, and e(1) and e(2) are stationary with mean zero, constant variance, no serial correlation, constant contemporaneous covariance, and uncorrelated with any of the right-hand side variables. When specified, dummy variables or a trend term are considered exogenous variables.

The VAR order p is the farthest lag for which the model's forecast residuals are minimum. When average forecast errors between models do not significantly differ, statistical parsimony dictates that the VAR model with minimum p be chosen. That is, as p increases, the number of additional lagged variables is multiplied by the number of endogenous variables since each equation is identically lagged, thus quickly reducing degrees of freedom.

VAR avoids bias due to simultaneity since each endogenous variable in the model is a function only of its own lagged values and those of all other endogenous variables. Thus ordinary least squares regression can be applied to each equation for estimation. Serial correlation is accounted for by the lagged dependent

variables. However, the disturbances e(1) and e(2) may be contemporaneously correlated such that a shock to one variable is transmitted or transferred to the other variable according to their covariance matrix. This multivariate interaction between equations is additional information which univariate models do not have, but which VAR takes advantage of through the impulse response function.

Impulse Response Analysis

An impulse response function measures marginal effects on Y(t) from a change to e(t). An example is the effect of one standard deviation change in the e(t) on current and future values of Y(t). It is a matrix of impact multipliers that determine the magnitude of change to other endogenous variables of an innovation or shock to an endogenous variable. In terms of CPI and MPI, it answers the question: What is the effect on CPI at time t, t+1, t+2, etc. induced by a unit exogenous shock to MPI at time t? For the bivariate VAR model above, an innovation in e(2) by one unit is equivalent to a unit change in x(t) as x(t-1), x(t-2), y(t-1), y(t-2) are predetermined. Future values of y(t) in the first equation are then impacted by the change in x(t) from the second equation according to the impulse response function. 1/

A graph of the impulse response function will trace the response of CPI to an impulse from MPI, for example, by one standard deviation shock to MPI. The response, whether positive or negative, will typically vary with respect to zero over the specified range of lags, peaking at a certain lag or range of lags. In theory, the response eventually dies out (moves toward zero) as the impact from farther lags slowly decays. This should be true for own-variable responses, such as changes to future CPI induced by a one standard deviation innovation in CPI(t). The dynamic multiplier is the collection of responses in Y(t) triggered by a given set of shocks to e(t).

Variance Decomposition

Another way to gauge the resulting impact of a disturbance in one equation is to ask the question: How much of the forecast error variance of y(t) is due to that disturbance? Variance decomposition explains how much of the movements in a variable is due to its own shock versus shocks to other variables. The forecast information conveyed is similar to that of impulse response function because both trace the overall effects of a shock. Either tool helps uncover the relative contribution of each variable in generating a model's forecasts.

A graph of variance decomposition shows the percentage of the total variance of a dependent variable that is due to itself and to other endogenous variables in the VAR model. If a shock in x(t) explains none of the forecast error variance of y(t), then y(t) is said to be exogenous over the given forecast period. At short horizons, it is usual for y(t) to explain most if its forecast error variance, then diminish over longer time lags. Thus the effect of x(t) on y(t) should, conversely, increase over time. While complementary to impulse response functions, variance decomposition does not reveal new information about dynamic feedback.

Predictive Causality

Since correlation does not necessarily imply causality, it may be useful to check for causality between variables if they are used together for forecasting. The Granger causality test can determine whether lagged values of x as a group causes y, or vice versa. This is one way of finding out if adding lagged values to the equation increases the probability of causation. For example, if an extra lag raises the F statistic of the Granger causality test of whether x causes y, then adding a lagged x variable to the model should reduce forecasts errors of y.

In VAR, at least one lag of a variable should have a significant coefficient in order to Granger-cause the dependent variable. The test answers the question: Does x contain enough information to forecast y? More specifically, can x(t-i) improve forecasts of y(t) for the given i lags? That is, x(t-i) has no predictive impact on y(t) if the following expectation functions equate:

$$E[y(t) \mid y(t-1), x(t-1)] = E[y(t) \mid y(t-1)] \text{ for all } t$$

If the F statistic for all lagged x is not significant, then y is said to be strictly exogenous such that a change in x has no effect on y for the given number of lags. The Granger causality test is also useful in checking whether the number of lags as specified in the VAR model is the same or close enough to that of the largest F value. The F statistic normally declines when more lags are added.

Estimating the Food CPI Models

Econometric software EViews (Version 3) was used in estimating the VAR models and in generating their dynamic forecasts. A first step in specifying a model is to examine a graph of the time series data of CPI and MPI or XRI. Trend, seasonality, and outlying points should be noted. Do the two time series closely track each other? A lead or lag relationship between them can more easily be discerned from a cross-correlogram, which would indicate at what monthly lags the correlations are highest and whether the correlations are negative or positive, if significant.

Model selection starts by specifying 1 lag (first-order VAR) and a constant. If the estimated coefficient of either endogenous variable is significant, a second lag should be tested, and so on. If the constant (intercept) is not significant, it should be discarded. The best fitting model is when the Akaike Information Criterion (AIC) and Schwarz Criterion (SIC) statistics, which are measures of forecast error variance, are minimum. In addition, the estimated model's number of lags should correspond closely with that of the maximum F statistic in the Granger causality test.

The VAR is performed on data levels, as opposed to first differences or other transformations, to avoid losing information about the time series, such as trend (deterministic) or seasonality, which can be specified as exogenous variables. The sample size of 120 monthly observations (10 years) is sufficiently large to asymptotically offset non-normal distribution effects of unit roots (e.g., due to stochastic trend) on the test statistics (p. 315, Diebold). 2/ Moreover, if the CPI forecast errors are white noise (stationary with mean zero, constant variance, and no serial correlation), then differencing the data to remove the unit root is unnecessary.

Once the VAR model is chosen, the impulse response function is graphed. When forecast errors of the model equations are correlated, as they usually are in VAR due to long-run cointegration between the endogenous variables, the impulse response graphs will show the dynamic pattern of responses in each variable to a one standard deviation innovation. To check the validity of a model, the residuals should be graphed. If they are white noise, then no additional modeling changes such as exogenous variables for trend, seasonality, or outliers are needed. Seasonality and outliers can be modeled by specifying dummy variables. In case the residuals are still nonstationary, or have significant autocorrelations, then a unit root is probably present and should be removed by first-differencing. In any case, the final residuals should exhibit these conditions:

$$E[e(t)] = E[e(t-s)],\ \text{var}[e(t)] = \text{var}[e(t-s)],\ \text{and } E[e(t)e(t-s)] = 0 \text{ for all lags } s.\ 3/$$

Case Study: Fish and Seafood CPI Model

A graph of the CPI and the Import Price Index for fish and seafood is shown below. Their monthly upward patterns appear to move together relatively closely. The cross-correlogram attests to the positive correlation between lagged MPI and CPI(t). Neither the graph nor the cross correlogram reveals the number of lags that would identify the best-fitting model. After specifying one lag, then two, the second-order VAR appears to provide the best fit since the AIC and SIC forecast error criteria are minimized. The estimated VAR(2) model is shown below along with the Granger causality test. Since the F statistic in the causality test is significant for the first null hypothesis, we reject noncausality from MPI to CPI. The test also indicates no evidence of feedback from CPI to MPI since the second null hypothesis is not significant. The F statistic decreases when a third or fourth lag is added to the model.

The graph of the impulse response function shows that an innovation to MPI produces increasing responses in CPI, building up from zero impact as the number of lags increases before leveling off after 20 lags. Conversely, an innovation to CPI elicits a smaller response in MPI. The own-variable dynamics correctly shows declining influence of an innovation in CPI(t-i) on subsequent CPI(t). Variance decomposition analysis shows that the percentage of variance in the CPI forecast errors explained by MPI increases monotonically over longer horizons, reflecting building up of effects over time. In contrast, the CPI error variance due to innovations to itself correctly starts at 100 percent then declines toward zero as impact diminishes at longer lags.

An inspection of the monthly CPI data for fish and seafood shows a seasonal upward tick in prices in January. Specifying a dummy variable for January over the sample period creates a corresponding spike in the graph of the forecast values below. The dynamic forecasts clearly exhibit strong autocorrelation, which is evident in the sizable positive impacts of the first and second lags for CPI. (Dynamic forecasts use forecast values for the lagged dependent variables.) Note that the estimated coefficient for MPI(t-1) has only about half the impact of CPI(t-2) and its contribution is statistically weak. Overall, the dynamic forecasts of the historical values are fairly accurate.

Finally, an examination of the static forecast residuals reveal white noise disturbances that look stationary. (Static forecasts use actual values for the lagged endogenous variables.) No remaining trend, seasonal, or cyclical pattern appears in the residuals. Likewise, the correlogram of the residuals indicates randomness and thus no unit roots. MPI was only marginally helpful in forecasting CPI for fish and seafood. Most of the dynamic influence on CPI in this case is from its own lagged values, as was initially expected. Nevertheless, if fish and seafood consumption in U.S. households is increasingly satisfied by imports, the impact of import prices on consumer prices should become stronger.

Case Study: Fats and Oils CPI Model

Fitting a VAR model to CPI for fats and oils is an example of dealing with outlying observations. The time series is characterized by a sharp price hike at the end of the sample period. Since the last month of the CPI data as well as the last two months of the exchange rate index declined, the spikes can be considered as outliers. The forecasts for CPI will be biased upward if, as expected, the dynamic forecasts generated by the VAR model follow the spike s implicit price acceleration. The out-of-sample forecasts therefore have a high initial value that will be carried over because of the model's strong autoregressive characteristic.

Finding a fit that discounts the effect of the outliers is not a straightforward process. The typical first step is to construct a dummy variable for the CPI outliers. However, the estimated coefficient for the dummy variable in this case was not significant. Likewise, a trend variable that may track an average path through

the data points was found to be not much different from zero. Finally, after noticing that the exchange rate index similarly exhibited two sharp spikes immediately before the CPI spikes, a dummy variable for the exchange rate spikes was tried instead. Not only was the dummy for XRI significant, the fitted dynamic model also provided lower initial CPI values for the out-of-sample forecasts, in line with ending values for both CPI and XRI data. As seen in the table of the data and forecasts below, projections of the fats and oils CPI were on target.

Evaluating the CPI Forecasts

For each of the food CPI categories, the average absolute error of the historical forecasts as a percentage of actual CPI is listed in the table provided below. Also, data for the first 4 months of the out-of-sample period are compared with the respective forecasts. The historical forecast results indicate highly accurate fits of the data by the VAR models--less than or equal to 5 percent average error and many below 2 percent. The out-of-sample forecasts are, so far, also fairly accurate--all less than 5 percent average error and many below 1 percent.

The VAR forecasts were able to predict a number of turning points in the out-of-sample data--that is, the models' forecasts rose when the data increased, or fell when they declined. However, the small or insignificant effects of MPI or XRI on CPI in most models ensured the predominant autoregressive effects of lagged CPIs on forecasts. This can be a disadvantage when a sharp turning point occurs as in the jump in fresh fruit prices in April 1999 or the dive in fresh vegetable prices in February 1999.

Average annual CPI forecasts for 1998, 1999, and 2000 are also provided in the table below to check if the predicted inflation rates for the food CPIs are reasonable. Fresh fruits show the highest projected price inflation (6 percent) for 1999. In contrast, average prices for meats and for fresh vegetables are forecast to decline in 1999. In 2000, alcoholic beverages and fats and oils show lower prices and the other inflation rates are 3 percent or less. Overall, the forecasts do not differ by a significant margin from the average CPI in the previous year.

The CPI forecasts and respective MPI or XRI forecasts for each food category are provided in the second table below. 4/ The MPI forecasts are actually real exchange rate forecasts weighted by import values. Exchange rate forecasts are used in generating out-of-sample forecasts of import prices since import prices in general are responsive to exchange rate changes of the dollar with respect to the currencies of the import sources. 5/

Summary and Conclusions

There is growing dependence of the domestic food market on international food trade and prices. World food prices are increasingly transmitted to domestic food prices as trade in food commodities continues to grow. However, trade projections and domestic price forecasting are often conducted independently, which can potentially result in inconsistent forecasts. In an effort to integrate trade and domestic forecasts, this paper demonstrates how international price and exchange rate indexes can be used in forecasting components of the domestic food CPI. In particular, it examines the extent to which food import prices have influenced food CPIs by estimating vector autoregression models that include food import prices.

The forecasts of consumer price indexes for food products using import prices or exchange rate indexes as predetermined variables in the estimated vector autoregression models were largely accurate, even out-of-sample. The dynamic time series process of the CPI was well reflected in the short-term forecasts, accounting to a high degree for lagged univariate effects. The strong autocorrelation of CPI values largely

dominated the cross-correlation effects of MPI or XRI. Since our ultimate objective is to generate accurate forecasts, and because time series analysis--a statistical approach--was employed, the regression or causal effects of MPI or XRI on CPI mattered to the extent they helped improve the forecasts.

The CPI data, despite apparent nonstationary characteristics and occasional seasonality, were relatively easy to fit with VAR models. The modeling procedure was fairly straightforward. Models with high R-squared and minimum residual covariance (Akaike or Schwarz information criteria) produced tight historical fits and the forecasts initially appear to be largely accurate. Nevertheless, additional information provided by the import price or exchange rate indexes had modest quantitative influence on CPI.

Although most imported food products are intermediate goods, more value-adding activity is performed in the importing country. However, value-adding costs, such as for labor and capital, do not fluctuate as much as import prices. Thus, short-term domestic price movements reflect import price changes more than the value-adding costs. Furthermore, the growing import content of U.S. food consumption increases the importance of import prices in determining domestic food prices. Hence, identifying food products that are more highly traded and influenced by international factors is important not only for domestic price forecasting, but also for trade outlook estimates. Greater consistency between forecasts of trade prices and trade outlook estimates should result.

Notes:

1/ The dynamic impact of innovations in e(t) on Y(t) in the general VAR model is derived from the set of coefficients, or impulse responses, estimated when the Y(t) are expressed exclusively in terms of e(t) by back substitution. The coefficients are then normalized by the standard deviation of the error term of the shocked variable until the resulting disturbances have unit normal distributions and zero covariance (Diebold, pp. 305-08).

2/ A stochastic or nonlinear trend pattern is usually removed by first differencing, while a deterministic or linear trend can be directly modeled by adding a linear trend variable in the model. See Chapter 4 of Frances (10).

3/ Nonsignificant regression coefficients (for lagged MPI or XRI) are not zeroed out in forecasting because they may be cointegrated with the CPI variable. That is, despite units roots in CPI and MPI or XRI (making the distribution of t-ratios non-normal), their linear regression is stationary. See Frances, pp. 201-2.

4/ MPI forecasts for the Other Prepared Foods and for Processed Fruits and Vegetables categories were computed from out-of-sample VAR projections since no import values were readily available to weight the real exchange rates.

5/ The magnitude of exchange rate pass-through to import prices for food commodities can be estimated by least-squares regression of import prices against exchange rates, which should yield an inverse relationship if the exchange rate is expressed in foreign currency units per dollar.

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Forecast Results

	Month	CPI	Forecast	% Absolute Error
1. Red meats and products	January 1999	102.9	103.2	0.3
	February 1999	103.8	103.3	0.5
Average historical forecast error:	March 1999	103.6	103.4	0.2
1.8 percent	April 1999	103.7	103.5	0.2
2. Fish and seafood	January 1999	107.0	109.1	2.0
	February 1999	107.4	109.2	1.7
Average historical forecast error:	March 1999	106.9	109.3	2.2
1.5 percent	April 1999	108.0	109.4	1.3
3. Dairy products	January 1999	121.4	119.2	1.8
	February 1999	122.2	119.8	2.0
Average historical forecast error:	March 1999	121.6	120.1	1.2
3.2 percent	April 1999	117.5	120.4	2.5
4. Fats and oils	January 1999	109.6	110.6	0.9
	February 1999	109.9	111.1	1.1
Average historical forecast error:	March 1999	108.8	111.5	2.5
5.1 percent	April 1999	108.5	111.9	3.1
5. Fresh fruits	January 1999	122.1	119.1	2.5
	February 1999	117.7	119.9	1.9
Average historical forecast error:	March 1999	117.6	119.1	1.3
3.8 percent	April 1999	124.2	119.0	4.2
6. Fresh vegetables	January 1999	116.3	116.1	0.2
	February 1999	108.7	113.9	4.8
Average historical forecast error:	March 1999	108.3	111.8	3.2
5.4 percent	April 1999	106.8	110.6	3.6
7. Processed fruits and vegetables	January 1999	111.4	109.5	1.7
	February 1999	111.1	109.9	1.1
Average historical forecast error:	March 1999	110.9	110.0	0.8
0.5 percent	April 1999	110.8	110.2	0.5
8. Cereals and bakery products	January 1999	110.0	109.2	0.7
	February 1999	109.8	109.5	0.3
Average historical forecast error:	March 1999	109.6	109.7	0.1
1.6 percent	April 1999	110.4	110.0	0.4
9. Sugar and sweets	January 1999	110.3	109.3	0.9
	February 1999	110.0	109.3	0.6
Average historical forecast error:	March 1999	109.8	109.8	0.0
1.1 percent	April 1999	110.3	110.1	0.2

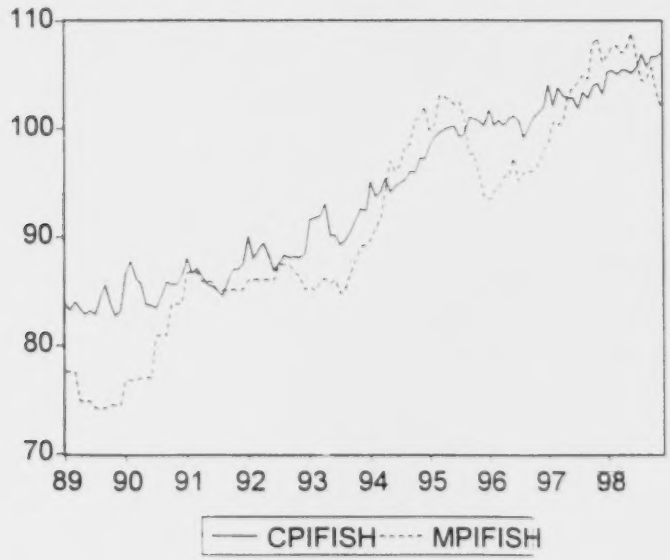
10. Other prepared foods	January 1999	111.0	110.7	0.3
	February 1999	111.3	110.8	0.4
Average historical forecast error:	March 1999	111.3	111.0	0.3
0.7 percent	April 1999	112.0	111.2	0.7
11. Nonalcoholic beverages	January 1999	101.3	99.5	1.8
	February 1999	102.1	99.5	2.5
Average historical forecast error:	March 1999	102.1	99.7	2.4
3.0 percent	April 1999	102.0	100.0	2.0
12. Alcoholic beverages	January 1999	108.9	108.8	0.1
	February 1999	109.6	109.5	0.1
Average historical forecast error:	March 1999	109.4	110.0	0.5
0.5 percent	April 1999	109.7	110.3	0.5

Out-of-Sample Forecasts of Food CPI and MPI or XRI; 1995=100

		Red Meats & Prods.	Fish and Seafood		Dairy Products		Fresh Fruits		Fresh Vegetables		Cereal & Bakery	
	CPI	MPI	CPI	MPI	CPI	XRI	CPI	MPI	CPI	MPI	CPI	XRI
1999:01	103.2	94.8	109.1	107.4	119.2	108.3	119.1	99.3	116.1	118.6	109.2	108.7
1999:02	103.3	94.8	109.2	107.4	119.8	108.3	119.9	99.3	113.9	118.6	109.5	108.7
1999:03	103.4	94.8	109.3	107.4	120.1	108.3	119.1	99.3	111.8	118.6	109.7	108.7
1999:04	103.5	94.0	109.4	105.2	120.4	108.9	119.0	99.6	110.6	119.0	110.0	109.1
1999:05	103.6	94.0	109.3	105.2	120.6	108.9	119.1	99.6	110.1	119.0	110.3	109.1
1999:06	103.6	94.0	109.3	105.2	120.8	108.9	118.9	99.6	110.0	119.0	110.5	109.1
1999:07	103.7	92.5	109.4	103.2	121.1	107.4	118.9	99.1	110.1	118.0	110.8	107.9
1999:08	103.7	92.5	109.2	103.2	121.4	107.4	118.8	99.1	110.3	118.0	111.0	107.9
1999:09	103.8	92.5	109.2	103.2	121.7	107.4	118.9	99.1	110.6	118.0	111.3	107.9
1999:10	103.9	90.5	109.2	101.6	122.0	104.1	118.8	98.3	110.9	116.5	111.5	106.0
1999:11	103.9	90.5	109.0	101.6	122.2	104.1	118.7	98.3	111.1	116.5	111.7	106.0
1999:12	104.0	90.5	109.0	101.6	122.5	104.1	121.1	98.3	111.4	116.5	111.9	106.0
2000:01	104.0	88.9	111.1	101.3	122.7	102.3	123.3	98.0	118.0	115.5	112.0	105.0
2000:02	104.1	88.9	110.5	101.3	123.0	102.3	122.6	98.0	116.6	115.5	112.2	105.0
2000:03	104.2	88.9	110.5	101.3	123.2	102.3	122.4	98.0	115.0	115.5	112.4	105.0
2000:04	104.2	87.6	110.4	100.2	123.5	101.1	122.4	97.7	114.2	114.9	112.5	104.1
2000:05	104.3	87.6	110.2	100.2	123.8	101.1	122.3	97.7	113.8	114.9	112.6	104.1
2000:06	104.4	87.6	110.0	100.2	124.1	101.1	122.3	97.7	113.8	114.9	112.8	104.1
2000:07	104.5	86.5	109.9	99.5	124.4	100.6	122.2	97.6	114.0	114.6	112.9	103.6
2000:08	104.5	86.5	109.7	99.5	124.7	100.6	122.1	97.6	114.2	114.6	113.0	103.6
2000:09	104.6	86.5	109.6	99.5	125.0	100.6	122.1	97.6	114.5	114.6	113.1	103.6
2000:10	104.7	85.6	109.4	98.8	125.2	100.1	122.0	97.4	114.8	114.3	113.3	103.0
2000:11	104.7	85.6	109.2	98.8	125.5	100.1	121.9	97.4	115.1	114.3	113.4	103.0
2000:12	105.2	85.6	109.1	98.8	125.8	100.1	124.1	97.4	115.4	114.3	113.5	103.0
Average CPI												
1998	104.6	change	105.9	change	113.5	change	112.6	change	111.8	change	108.2	change
1999	103.6	-1.0%	109.2	3.1%	121.0	6.6%	119.2	5.9%	111.4	-0.4%	110.6	2.2%
2000	104.5	0.9%	110.0	0.7%	124.2	2.6%	122.5	2.8%	114.9	3.1%	112.8	2.0%

			Sugar and Sweets		Nonalcoholic Beverages		Alcoholic Beverages		Fats and Oils		Other Prepared Food	Processed Fruits & Vegetables	
	CPI	XRI	CPI	XRI	CPI	MPI	CPI	XRI	CPI	MPI	CPI	MPI
1999:01	109.3	111.8	99.5	117.1	108.8	108.1	110.6	114.4	110.7	95.0	109.5	96.5
1999:02	109.3	111.8	99.5	117.1	109.5	108.1	111.1	114.4	110.8	95.2	109.9	96.7
1999:03	109.8	111.8	99.7	117.1	110.0	108.1	111.5	114.4	111.0	95.3	110.0	96.8
1999:04	110.1	110.6	100.0	114.0	110.3	109.4	111.9	114.4	111.2	95.5	110.2	97.0
1999:05	110.2	110.6	100.0	114.0	110.8	109.4	112.3	114.4	111.5	95.6	110.3	97.1
1999:06	110.4	110.6	99.9	114.0	111.2	109.4	112.6	114.4	111.7	95.8	110.5	97.3
1999:07	110.6	109.2	99.8	111.4	111.5	108.2	112.9	113.2	111.9	96.0	110.7	97.5
1999:08	110.8	109.2	99.8	111.4	111.6	108.2	113.0	113.2	112.1	96.1	110.8	97.6
1999:09	111.0	109.2	99.8	111.4	111.7	108.2	113.2	113.2	112.3	96.3	111.0	97.8
1999:10	111.2	107.6	99.8	107.7	111.8	104.8	113.3	110.9	112.5	96.4	111.1	98.0
1999:11	111.4	107.6	100.0	107.7	111.3	104.8	113.1	110.9	112.7	96.6	111.3	98.1
1999:12	111.5	107.6	100.2	107.7	111.0	104.8	113.0	110.9	113.0	96.8	111.5	98.3
2000:01	111.6	106.4	100.3	107.1	110.9	103.1	113.0	109.6	113.2	96.9	111.6	98.5
2000:02	111.8	106.4	100.6	107.1	110.5	103.1	112.7	109.6	113.4	97.1	111.8	98.6
2000:03	111.9	106.4	101.0	107.1	110.3	103.1	112.6	109.6	113.6	97.2	111.9	98.8
2000:04	112.1	105.4	101.4	105.2	110.2	102.1	112.4	108.6	113.8	97.4	112.1	98.9
2000:05	112.3	105.4	101.7	105.2	109.9	102.1	112.2	108.6	114.0	97.6	112.3	99.1
2000:06	112.4	105.4	102.1	105.2	109.8	102.1	111.9	108.6	114.3	97.7	112.4	99.3
2000:07	112.5	104.6	102.4	104.6	109.8	101.7	111.8	108.1	114.5	97.9	112.6	99.4
2000:08	112.7	104.6	102.8	104.6	109.7	101.7	111.5	108.1	114.7	98.1	112.8	99.6
2000:09	112.8	104.6	103.2	104.6	109.6	101.7	111.3	108.1	114.9	98.3	112.9	99.8
2000:10	112.9	104.8	103.5	103.9	109.7	101.5	111.2	107.5	115.1	98.4	113.1	99.9
2000:11	113.1	104.8	103.9	103.9	109.7	101.5	110.9	107.5	115.3	98.6	113.3	100.1
2000:12	113.2	104.8	104.2	103.9	109.7	101.5	110.7	107.5	115.6	98.8	113.4	100.3
Average CPI												
1998	109.2	change	101.0	change	107.7	change	107.0	change	109.5	change	109.4	change
1999	110.5	1.2%	99.8	1.2%	110.8	2.9%	112.4	5.0%	111.8	2.1%	110.6	1.1%
2000	112.5	1.8%	102.3	2.5%	110.0	-0.7%	111.9	-0.4%	114.4	2.3%	112.5	1.7%

Consumer and Import Price Indexes for Fish and Seafood



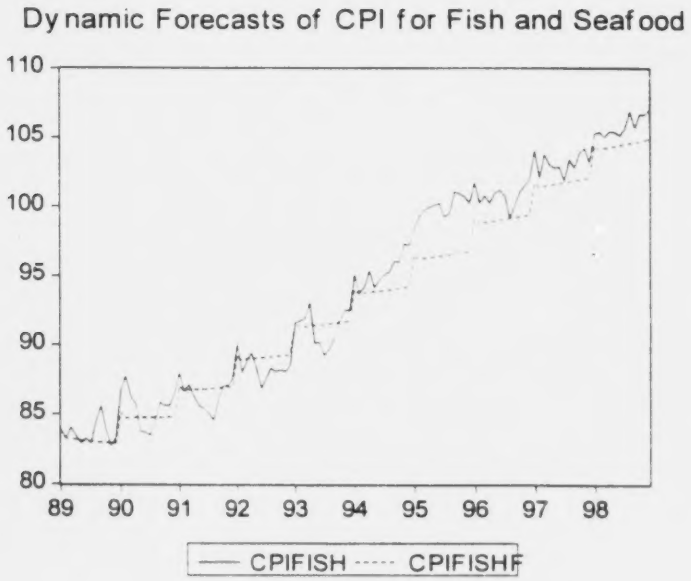
VAR Estimation Results
Sample(adjusted): 1989:03 1998:12
Included observations: 118 after adjusting endpoints
Standard errors & t-statistics in parentheses

	CPIFISH	MPIFISH
CPIFISH(-1)	0.787854	0.132274
	(0.07691)	(0.10601)
	(10.2435)	(1.24771)
CPIFISH(-2)	0.180813	-0.089322
	(0.07634)	(0.10522)
	(2.36864)	(-0.84892)
MPIFISH(-1)	0.097197	1.102282
	(0.06836)	(0.09422)
	(1.42188)	(11.6988)
MPIFISH(-2)	-0.062520	-0.144617
	(0.06865)	(0.09462)
	(-0.91070)	(-1.52834)
DUM_JAN	2.216353	0.623743
	(0.30775)	(0.42419)
	(7.20184)	(1.47044)
R-squared	0.987389	0.985848
Adj. R-squared	0.986942	0.985347
Sum sq. resids	87.24951	165.7627
S.E. equation	0.878703	1.211168
F-statistic	2211.789	1967.894
Log likelihood	-149.6219	-187.4872
Akaike AIC	2.620710	3.262496
Schwarz SC	2.738112	3.379897
Mean dependent	94.23654	91.81271
S.D. dependent	7.689661	10.00546
Determinant Residual Covariance		1.034922
Log Likelihood		-336.8948
Akaike Information Criteria		5.879572
Schwarz Criteria		6.114376

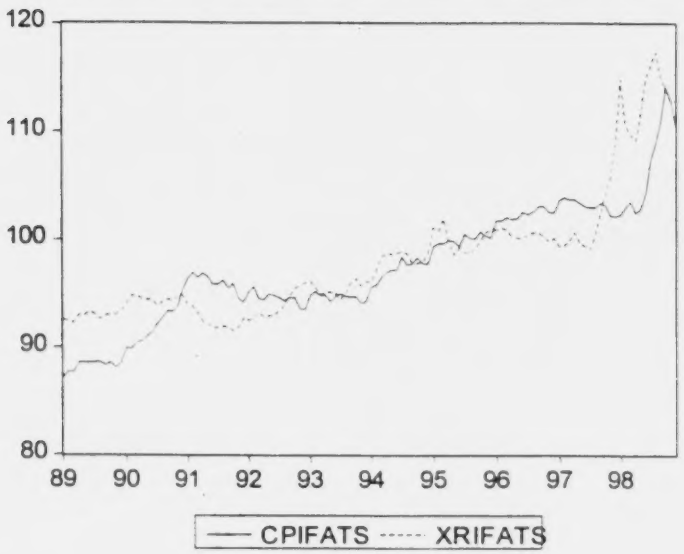
Pairwise Granger Causality Tests

Sample: 1989:01 1998:12
Lags: 2

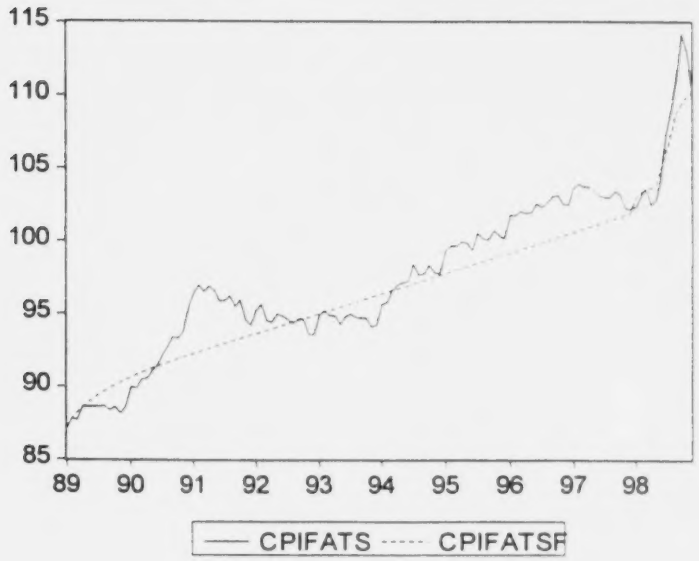
Null Hypothesis:	Obs	F-Statistic	Probability
CPIFISH does not Granger Cause MPIFISH	118	0.88951	0.41371
MPIFISH does not Granger Cause CPIFISH		1.97813	0.14309



CPI and Exchange Rate Index for Fats and Oils



Dynamic Forecasts of CPI for Fats and Oils



19th International Symposium on Forecasting
Washington, DC

June 27-30, 1999

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19th International Symposium on Forecasting

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FORECASTING IN THE U.S. GOVERNMENT—Featured Session

A Brief History of the Federal Forecasters Conference,
Karen S. Hamrick, Economic Research Service, U.S. Department of Agriculture

The Bureau of Labor Statistics Employment Projections Program,
Charles T. Bowman, Bureau of Labor Statistics, U.S. Department of Labor

The National Center for Education Statistics Projections Program,
Debra E. Gerald, National Center for Education Statistics,
U.S. Department of Education

Forecasting in the U.S. Department of Agriculture,
Frederic Surls, Economic Research Service, U.S. Department of Agriculture

Forecasting in the U.S. Federal Government

Karen S. Hamrick
Economic Research Service
U.S. Department of Agriculture

A Brief History of the Federal Forecasters Conference

Forecasting in the federal government encompasses a wide variety of disciplines, techniques, and purposes. Forecasts produced by the federal government include population projections, employment projections, macroeconomic forecasts, budget projections, price forecasts, weather forecasts, and scenarios on various proposed policy changes. Federal forecasters are frequently called upon to address emerging and complex issues in order to provide information for policy decisions.

In the late 1980s, the National Center for Education Statistics saw a need to bring together forecasters across the federal government to share knowledge and skills on forecasting. While it was recognized that forecasters from different agencies informally discussed data and forecasting methods, there was no organized network that allowed federal forecasters to share information. In addition, there were at that time few textbooks or courses on forecasting; most forecasters learned on the job and from each other. NCES addressed these needs by sponsoring the first and second Federal Forecasters Conferences (1988 and 1989). These two conferences were an important first step in organizing federal government employees representing a broad spectrum of disciplines and varying program responsibilities.

The Federal Forecasters Conference has continued as a partnership of forecasters from various federal agencies. The Conference operates with a charter that states the conference's goals are: to provide a forum for forecasters to exchange information on data issues and quality, forecast methodologies, and evaluation techniques; to promote an ongoing dialogue about various forecasting topics among forecasters from various discipline; to build a core network of forecasters whose collaboration furthers the use of forecasting as an important planning tool in the 21st century; and to expand the network of forecasters by seeking sponsorship from agencies in all parts of the Government.

With support from cosponsoring agencies, eight conferences were held over 1990-99. Conference attendance has averaged 150 people, representing 40-50 agencies. Over the past 10 meetings, the conference themes have included forecasting and public policy, the role of the federal forecasters, forecasting with diminishing resources, and coordinating and networking on the information highway. This partnership of agencies continues as the 2000 conference is now being planned.

This year's conference was planned in collaboration with the International Institute of Forecasters, so that the Federal Forecasters Conference and the International Symposium on Forecasting would be back to back, encouraging greater interaction among federal, academic, and private sector forecasters.

Forecasting in the U.S. Government

The U.S. Federal Government is a major provider of forecasts for use by government and private sector decision makers. Many forecasting programs have changed dramatically and some have been disbanded over the last few years due to declining budgets and changing priorities. Yet still, there seems to be an insatiable demand for the forecasting products that agencies produce. In this session, the panelists–each of whom directs a forecasting program–looked at the role of the public sector in an information economy and how forecasters can provide relevant and useful information to policymakers and the public.

Charles T. Bowman is Chief of the Division of Industry Employment Projections at the Bureau of Labor Statistics, and has directed that program for 20 years. Debra E. Gerald leads the education enrollment projections program at the National Center for Education Statistics, and her efforts have been central and significant in the success of the 10 Federal Forecasters Conferences. Frederic M. Surls is Deputy Director for Market Analysis and Outlook, Markets and Trade Economics Division, and coordinates the outlook program at the Economic Research Service.

The Bureau of Labor Statistics Employment Projections Program

Charles T. Bowman, U.S. Bureau of Labor Statistics

The BLS projections program began in the late 1940's to provide information to help World War II veterans plan their careers. While the scope of the projections has been broadened over the years, career guidance remains its major focus. The *Occupational Outlook Handbook*, now in its 50th year, is without doubt the most widely used source of information about future job prospects in the United States.

Currently, the Bureau develops a new set of projections every other year. The most recent was released in late 1997 and covers the 1996 to 2006 period. Included are projections of the labor force by age, sex and race and employment by industry and detailed occupation. A new set of projections covering the 1998-2008 period is due out later this year.

The projections are released in a series of publications beginning with a special issue of the *Monthly Labor Review* in November of odd-numbered years. New editions of the *Occupational Outlook Handbook* and *Career Guide to Industries* are released shortly thereafter. These publications provide a wealth of information on the outlook for employment in specific industries and occupations over the next ten years as well as on educational and training requirements, working conditions and wages. In addition, more technical publications such as *Occupational Projections and Training Data* and Bulletins exploring specific areas of the projections in greater depth are also released at this time.

Job seekers together with the counselors and others involved in assisting them are by far the major users of the information produced by the BLS program. Other important users include State and local governments who develop their own employment projections based on BLS results and those involved in planning and developing education and training programs. The projections also serve government and others as an important resource for analyzing a variety of employment policy issues.

The BLS projections program has continuously evolved over the past 50 years in response to the changing needs of users and the increasing complexity of the job market. The last ten years have seen particularly far-reaching changes as computer technology has fundamentally changed the way projections are done and the way in which results are disseminated to users. Through Internet technology the entire process of forecasting from modelling to publication has been streamlined. This in turn has helped BLS to deal with a problem facing most programs in government today, the need to meet increasing demands with fewer and fewer resources. Computer technology is also changing the way BLS results reach the user as internet access rapidly replaces more traditional media and makes possible new and more flexible distribution methods.

We expect that the next 10 years will bring additional challenges. The increasing pace of technological change introduces new uncertainty into the projection process and will require us to rethink the way in which the forecasts are made. The Workforce Investment Act of 1998 places new responsibilities on BLS to aid the states in their employment forecasting efforts and to make employment projections more accessible and relevant to job-seekers. These and other challenges coincide with an expectation of limited resources. The greatest challenge of all will be to find ways to increase the quality and usefulness of BLS projections in the face of these limitations.

The National Center for Education Statistics Projections Program

Debra E. Gerald
National Center for Education Statistics
U.S. Department of Education

The National Center for Education Statistics (NCES) is the statistical arm of the U.S. Department of Education. The forecasting program began in 1964. The program has four primary functions. These are:

--to project key education statistics for policy planning
--to perform ongoing model development
--to conduct evaluations of past projections
--to provide consultation on projection methodology

The projections are published on an annual basis and appear in *Projections of Education Statistics to 2008*. Also available is a summary of the projections in a pocket-sized folder entitled *Pocket Projections 2008*. Under elementary and secondary education, the NCES program projects the following education statistics: (1) elementary and secondary enrollment; (2) high school graduates; (3) classroom teachers/salaries; (4) public current expenditures; and (5) state public enrollment and high school graduates. For higher education, NCES projects the following education statistics: (1) higher education enrollment; (2) earned degrees by level; and (3) current-fund expenditures.

Several data sources are used to develop projections of education statistics. The education statistics that are projected come from the institutional surveys conducted by the National Center for Education Statistics. The common Core of Data survey collects statistics from the elementary and secondary schools and the Integrated Postsecondary Education Data System collects statistics from the colleges and universities. Population data are obtained from the U.S. Bureau of the Census' Current Population Survey. Salary data come from the National Education Association. Macroeconomic data are from Standard and Poor's DRI. The projections are consistent with the Census Bureau Middle series, which assume a fertility rate of 2.10 births per woman by the year 2008, a net immigration of 820,000 per year, and a further reduction in the mortality rate. A number of forecasting techniques are used to develop projections. These include the cohort-survival technique, single exponential smoothing, double exponential smoothing, and multiple linear regression.

Demographic changes over the next ten years will have a profound impact on projected trends in education statistics. For the school-age populations, the 5- to 13-year-olds are projected to grow by 3 percent. On the other hand, the 14- to 17-year-old population is projected to increase be 13 percent. Because of the increase in the number of annual births since 1977, the baby boomlet will have an impact on school enrollments. Over the projection period, there will be record levels of elementary and secondary enrollment in the United States. The 18-year-old population will grow by 22 percent. The traditional college-age population, 18- to 24-year-olds, is projected to increase by 18 percent. Most of these students will be enrolled full-time in college. Thus, full-time enrollment is projected to grow faster than part-time enrollment. In contrast, the older college-age populations are projected to show little growth or decline. The 25- to 29-year-olds are projected to increase by 2 percent, while the 30- to 34-year-old and 35- to 44-year-old populations will decline by 17 and 8 percent respectively.

The mission of NCES is to gather and disseminate statistics related to education to inform policymakers about ongoing and emerging issues. Users of projections of education statistics come from a number of organizations. They include federal, state, and local governments, industry, business, professional associations, the education community, media, and the public. To meet the demand for other projections of education statistics, NCES is developing models to project higher education enrollment by race/ethnicity and bachelor's degrees by field.

Forecasting in the US Department of Agriculture *

Frederic Surls
Economic Research Service
U.S. Department of Agriculture

The USDA Program

The Department of Agriculture has an extensive forecasting program that produces both short-run (1-2 year) forecasts and long-run (10 year) projections of commodity markets and performance of the agricultural sector. The Departmental forecasting program began about 75 years ago. At that time, the major objective of the program was to level the information playing field, increase market efficiency, and reduce price volatility.

This public good function remains important, but the Departmental forecasts are now critical to Departmental and other governmental policies makers for decisions about budget expenditures, agricultural policy, and trade policy. And the Departmental forecasts and supporting models provide the base and tools for a variety of "what if" scenarios about alternative policies or shocks to the system.

The Department forecasts key indicators of sector performance. The forecasts cover (1) commodity market supply, use, stocks, and prices for major commodities; (2) international market supply, use, and stocks, which are developed beginning with country-level estimates for more than 100 countries and a large number of commodities; (3) farm income; (4) farm financial conditions; (5) food prices; and (6) U.S. agricultural exports and imports. The short-run commodity market forecasts are prepared monthly. A full set of 10-year projections are prepared annually, and timed to the Federal government budget process.

The Departmental forecasting and projections process is an inter-agency activity that draws for expertise throughout the Department. The interagency activity ensures that all viewpoints are considered and that USDA forecasts and projections are agreed on and used throughout the Department. Forecasts and projections depend on both models and on informed judgement of Departmental analysts.

USDA makes a major commitment to the credibility and objectivity of its forecasts and projections. To ensure equal access to market sensitive data and analysis, key reports are prepared behind locked doors and are released at preannounced times. The Department also attempts to insulate the forecasting process from political influences.

The Department devotes substantial resources to information collection, data collection, analysis, and development of models and other analytical tools for analysis. In addition to the forecasts themselves, USDA agencies make the underlying data bases, analysis, and model documentation available to all users inside and outside the Government in both publications and electronic formats. This public investment in domestic and international data and analysis forms a key part of the knowledge base supporting public and private sector analysis and decision making for agriculture.

Pressures for Change in USDA Forecasting and Projection Activity

Like most other public sector information providers, USDA faces a growing set of challenges to its forecasting program. USDA, along with other government agencies, faces resource constraints. Funding, at least in real terms, for forecasting is declining in USDA agencies involved in the interagency estimates process. In addition, a number of agencies are seeing demands for analysis broaden as consumer, environmental, biotechnology, and trade issues increasingly compete for scarce resources with traditional analysis of production agriculture.

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* Panel presentation to *Forecasting in the Federal Government*, a session at the International Symposium on Forecasting, Washington D.C., June 28, 1999. The author is Deputy Director for Market Analysis and Outlook, Markets and Trade Economics Division.

Industry changes are also having an impact on USDA information and forecasting programs. Farmers are increasingly able to produce a much broader range of product characteristics than the standard grades that have been the norm. Production for specific traits moves more transactions out of markets and into vertical chains that link input suppliers, producers, and processors through contracts rather than markets. In the emerging industrialized agriculture, less information is available publicly, the role of traditional markets may diminish, and the type of information needed from the public sector may change.

How is USDA Forecasting and Projections Work Responding?

USDA forecasting programs and related data and information activities have been undergoing substantial change. First, over the last decade, computerization of data and publications and of analysis and forecasting has made large advances in productivity possible. Because of these gains, smaller staffs are now able to do more than larger staffs did a decade ago. This process will continue in coming years as dissemination of data, information, and forecasts becomes almost exclusively internet-based.

Second, USDA is currently evaluating its interagency estimates process in an effort to increase its efficiency. This offers the potential for maintaining the quality of the forecasting program as resources continue to decline across the agencies involved in the process.

Third, the Department is exploring new approaches to collaboration with University forecasters and analysts, again with the objective of maintaining the quality of our forecasting program.

Finally, The Department's Economic Research Service has begun a wide-ranging study of changing needs for and use of information on agricultural markets. Studies like this and improved customer contact are critical parts of USDA's efforts to understand the market for its information, adjust the program as the market changes, and make the best use of resources available for market analysis.

OTHER FORECASTING TOPICS

An Econometric Approach to Forecasting Environmental Conflict,
Katherine S. Carson, United States Air Force Academy

I. S. O. (In Search of) Prediction Yardsticks via Dynamic Programming,
Elliot Levy, U.S. Department of Commerce

Predicting Environmental Security Trends in Africa: A Proto-Type
Monitoring System of Environmental and Political Problems in Southern Africa,
Helen E. Purkitt, U.S. Naval Academy

The "Ten Suggestions" on How to Teach Forecasting to Adults:
What Your Parents Should Have Told You About Teaching Adults,
David Torgerson, Economic Research Service, U.S. Department of Agriculture

A Preliminary Evaluation of USDA's Export Forecasts,
Stephen A. MacDonald, Economic Research Service, U.S. Department of Agriculture

AN ECONOMETRIC APPROACH TO FORECASTING ENVIRONMENTAL CONFLICT

Katherine S. Carson, United States Air Force Academy

> All this came upon them with the late war, which was begun by the Athenians and the Peloponnesians by the dissolution of the thirty years' truce made after the conquest of Euboea. To the question of why they broke the treaty, I answer by placing first an account of their grounds of complaint and points of difference, that no one may ever have to ask the immediate cause which plunged the Hellenes into a war of such magnitude. The real cause I consider to be the one which was formally most kept out of sight. – Thucydides, The Peloponnesian War, Book I, Chapter 23 (Random House, 1982, p. 14)

Inquiry into the underlying causes of war has been around for as long as war itself. Typical analyses have focused on political variables such as the formation of alliances and balances of power. Recently, scholars have begun to examine the relationship between environmental scarcity and war. They theorize that as populations increase, so will the pressure on such resources as water, soil, and forests. Such pressures may generate conflicts. In fact, some argue that environmental pressures already play a role in some conflicts. In Rwanda, it appears that the effects of food scarcity aggravated existing tensions and weakened the legitimacy of the regime, adding fuel to the fire (Percival and Homer-Dixon, 1996). In addition, disagreements over the allocation and use of water have long played a role in the tensions between the Israelis and the Palestinians (Homer-Dixon and Blitt, 1998).

Case studies such as these point to the existence of a relationship between environmental scarcity and conflict. Recently, economists have begun to examine this relationship in the context of dynamic growth models. At the same time, scholars have begun a more systematic search for the presence of these relationships in the world using statistical models to both test and inform the theory. The purpose of this study is to exploit the variation that exists in the world in both levels of conflict and environmental degradation to establish which environmental variables, if any, play a role in generating conflicts. Probit, logit, and ordered logit and probit models of conflict and environmental decay are estimated using cross-sectional data from the *World Resources Institute* and *Political Research Services*. The models are then used to predict probabilities of levels of conflict using the most recent data from the *World Resources Institute*. The results indicate that certain environmental variables are predictive of the level of conflict in a region. Water supply, food supply, deforestation, and population density are consistent significant predictors of conflict. These results also point to the need for improved data to better model the relationship between the environment and conflict. Data derived from a Geographical Information System (GIS) would be particularly useful in shedding light on the complex relationship between the environment and conflict.

The following sections contain a review of the theoretical and empirical literature on the relationship between the environment and conflict. A description of the data and methodology, results, and conclusions and recommendations for future research follow.

DYNAMIC ECONOMIC MODELS

Although case studies provide evidence that environmental scarcities can generate conflict, it is difficult to generalize the results from these studies. If the goal is to forecast future conflicts, researchers must provide a general description of the environmental conditions that may lead to conflict. Dynamic economic models provide a framework in which such general results can be derived.

Although Brander and Taylor (1998) do not explicitly include conflict in their model of renewable resource use and population growth, their model illustrates how overuse of natural resources can lead to the decline of a civilization, such as that which happened on Easter Island during the 14th and 15th centuries. The authors argue that violence may be the result of a civilization's decline, rather than the cause of it. They hypothesize that their model may be applicable to the 1994 conflict in Rwanda as well as other modern conflicts.

Maxwell and Reuveny (1999) expand the Brander and Taylor (1998) model of renewable resource and population interaction to explicitly include the possibility of political conflict generated by per capita resource scarcity. Their model recognizes the fact that conflicts have feedback effects both on the population and on the stocks of natural resources. The degree and magnitude of these feedback effects provide information on both the severity and frequency of conflict, as well as information about the state of the region after the conflict subsides.

The basic model describes a population that engages in both primary extractive production (harvesting the renewable resource) and secondary production. Both the population and the renewable resource grow at

constant rates. Consumption and production levels are determined using utility and profit maximizing rules. This general equilibrium economic-ecological model in which the environment is a source of individual well being can be solved for the equilibrium levels of population, natural resource stocks, and secondary goods. In this model, conflict arises when the per capita levels of the natural resource are low. Maxwell and Reuveny (1999, p. 2) employ this model to address the following six questions:

1. How likely is it that conflict will erupt?
2. If it does, what are the factors that determine its length?
3. Will political conflict due to environmental scarcity come to an end?
4. If it does end, are additional conflicts possible?
5. What are the consequences of violence due to environmental degradation?
6. Which policies can reduce the vulnerability to conflict due to environmental scarcity?

The authors find that there are three main effects of conflict. First, conflict diverts resources (labor and capital) out of productive activities. As a result, both the harvest rate of the natural resource and the production of secondary commodities are reduced. Second, conflict increases the death rate of the population. Depending on the net effect on the overall population growth rate, this outcome may reduce pressure on the natural resource. Finally, conflict may cause direct destruction of the natural resource as a side effect of battle. The relative magnitudes of these effects determine the state of the region after the conflict has ended. Maxwell and Reuveny's results describe what factors are likely to increase the probability for conflict as well as its duration, severity, and frequency. In general, the results seem to conform to observations from case study research. In addition, the inclusion of feedback effects from conflict back to the ecological-economic system has important implications for empirical research. These implications will be discussed further below.

Statistical Modeling of Conflict

Statistical models of conflict differ from case study approaches in that they attempt to isolate those factors that are generalizable across space and time. Whereas case studies examine the particular causes of a particular conflict, statistical studies search for the common themes that are present in many conflicts. If such common themes are present and identified, their appearance in the future may point to the potential for conflict to emerge. If addressed in time, the conflict may be prevented. Three of the best examples of statistical studies of conflict are those of Richardson (1960) (as described by Wilkinson (1980)), Singer and Small (1972), and Choucri and North (1975).

Lewis Fry Richardson (1881-1953) is perhaps the first to take a systematic, mathematical approach to the study of armed conflict. He examines wars that terminated between 1820 and 1952 and classifies them based on the number, distribution, and type of actors involved, and the magnitude and duration of the conflict. In explaining the average characteristics of conflicts that occurred during this period, Richardson's goal is to identify the indicators of war so that their recognition might avert future conflicts.

Perhaps the most well known statistical study of war is Singer and Small's (1972) correlates of war project. The project is designed to identify the variables that were most frequently associated with the onset of war during the 150 years since the Congress of Vienna (1815). The goal of the project is to determine which factors distinguish those disputes that result in war from those that end in a less violent manner. Both Richardson's and Singer and Small's studies employ relatively simple statistical techniques such as correlation analysis, simple regressions, count data, and fitting distributions to observed data. Choucri and North (1975) take a more rigorous econometric approach to studying the causes of World War I.

Choucri and North (1975) use a simultaneous equations approach to modeling the conditions present in Great Britain, France, Germany, Russia, Italy, and Austria-Hungary from 1870 until the eve of World War I (1914). They argue that there are three major processes that generate conflict and warfare: domestic growth and external expansion of interests; competition for resources, markets, superiority in arms and strategic advantage; and the dynamics of crisis (p. 14). Although the authors to not employ environmental variables to represent these processes, it is clear how environmental variables enter into the processes of domestic growth and competition for resources. Choucri and North estimate a system of five equations for each country over the 45-year time period. Their model includes simple dynamic feedback elements. However, given the level of interaction between the sample countries over the specified time period, it is unclear why they choose to estimate individual country equations rather than to apply a panel data approach. Nevertheless, their approach represents a step up from previous statistical studies of conflict.

All of these studies tend to focus on the political and economic conditions that precede or coincide with conflict. None of them consider environmental

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conditions directly, although some do incorporate such variables as national income or population. A new study by Hauge and Ellingsen (1998) is perhaps the first to incorporate environmental variables into the statistical study of conflict. The authors estimate a logit model using conflict data from Singer and Small (1994) and Wallensteen and Sollenberg (1997). The independent variables measure deforestation, soil erosion, and freshwater supply. Because conflict also arises out of existing social and political conditions in a country, the authors include variables for income inequality, per capita GNP, and type of government to control for these factors. The unit of analysis is a country-year. The authors recognize that the panel nature of their data set is likely to induce autocorrelation into the model. They include a lagged value of the dependent variable in an attempt to correct for this effect. However, this correction is unlikely to remove all of the time-dependent effects. It is unclear why the authors do not estimate a panel probit or panel logit model. Furthermore, the authors create indicator variables to measure all of the environmental and political conditions listed above. Given that the actual units of many of these variables are available, is unclear why they choose to remove much of the detail and variability from their data through the creation of indicator variables. Finally, many of their environmental variables are time-invariant. They use values from the early 1990s to explain the presence of conflict throughout the sample period. It is unclear how present environmental conditions can affect past conflicts. A similar model by Tir and Diehl (1998) that examines the relationship between population variables and conflict suffers from many of the same criticisms, primarily the failure to account for the panel nature of their data using a panel logit or probit estimation technique such as that in Maddala (1993). Clearly a panel data or simultaneous equations model that captures the dynamic feedback effects between the environment and conflict as described by Maxwell and Reuveny (1999) is the preferred econometric methodology. However, the data does not exist to support this type of analysis.

This study seeks to exploit the systematic differences between countries with high and low levels of conflict and varying levels of environmental quality to examine the links between environmental quality and conflict in a cross-sectional framework. As with all statistical studies, the goal of this study is to uncover the average relationship between environmental variables and conflict and to discover which variables may make a country or region more or less conflict-prone. Probit, logit and ordered probit and logit models of conflict are estimated using data from *World Resources 1996-97*. Forecasts of future conflict levels are then generated using data from *World Resources 1998-99*. Because this is a static model, the relationship between environmental conditions and conflict is assumed to be time-invariant. Clearly, to the extent that the structural conditions of an economy change over time, this assumption is false. An obvious extension of this model is to include dynamic feedback effects through either a simultaneous equations or panel data approach, data permitting. Although one of the results of this inquiry is a forecast of the probability that a country experiences a given level of conflict, these results do not pinpoint the exact time or location of the next environmentally-motivated conflict. The section that follows describes the data and methodology employed to generate the forecasts.

Data and Methodology

The level of threat or the potential for conflict that a nation poses is a latent or unobserved variable in that it is not directly measurable on a continuous scale. It is possible, however, to construct indicator variables to represent the underlying latent threat variable. The construction of such variables is the principle behind limited-dependent variable models in econometrics. In the simplest case, the indicator variable is a binary variable of the form: 0 if a country is not a threat, 1 if a country is a threat. If we allow y^* to represent the latent variable measuring actual threat, and y to be the binary indicator variable, then values are assigned to y as follows:

$$\begin{aligned} y &= 0 \text{ if } y^* \le 0 \\ y &= 1 \text{ otherwise} \end{aligned} \qquad (1)$$

where the true underlying model for y^* is:

$$\mathbf{y}^* = \beta\mathbf{X} + \varepsilon \qquad (2)$$

y^* is an n x 1 vector of the threat that each country poses, X is an n x k matrix of explanatory variables, in this case variables reflecting the level of environmental stress in a nation, β is a k x 1 vector of parameters that indicate the effect of the explanatory variables on the level of conflict, and ε is an n x 1 vector of error terms reflecting individual deviations from mean behavior in the population. If it were possible to observe y^*, one could simply run a standard linear regression using ordinary least squares (OLS) to determine the values of the coefficients. However, because the observed indicator variable is discrete, OLS is not applicable. Two models are common. If ε is assumed to have a standard normal distribution, then a probit model is estimated. If ε is assumed to have an extreme value distribution, then a logit model is appropriate. In either

case, a likelihood function is specified that describes the probability of y given the values of the explanatory variables. Maximum likelihood estimation is then used to estimate the coefficients.

In many cases the indicator can take on a number of discrete values, indicating the level of threat or conflict that a nation poses. The underlying model for the latent variable is the same, but the indicator variable takes the form:

$$\begin{aligned} &y = 0 \text{ if } y^* \le 0 \\ &y = 1 \text{ if } 0 < y^* \le \mu_1 \\ &y = 2 \text{ if } \mu_1 < y^* \le \mu_2 \\ &\vdots \\ &y = J \text{ if } \mu_{J-1} \le y^* \end{aligned} \tag{3}$$

If the assumption is that the error terms have a standard normal distribution, then the model is an ordered probit model. The log-likelihood function for this model is:

$$\log L = \sum_{i=1}^{n} \sum_{j=1}^{k} Z_{ij} \log[\Phi(\mu_j - \beta' x_i) - \Phi(\mu_{j-1} - \beta' x_i)] \tag{4}$$

Where Z_{ij} is one if observation i is in category j and zero otherwise. Φ is the cumulative normal density function. The ordered logit model is similar except that the underlying assumption is that the error terms follow a logistic distribution. For well-behaved data, results are usually very similar from logit and probit models. Note that maximum-likelihood estimation of this function will result in computed values for both the regression coefficients (the β's) and the values establishing the boundaries for the level of conflict categories (the μ's). The expression inside the square brackets is the probability that observation i is in category j.

Four models are estimated for this study. In the first two, probit and logit, the dependent variable is either 0, no threat of conflict, or 1, a threat of conflict. In the third and fourth models, the dependent variable is a discrete variable ranging from 0 to 3, where 0 represents a low level of conflict and 3 represents a very high level of conflict. The models estimate the probability that a country will fall into each conflict category.

The dependent variable data is the Coplin-O'Leary 18-month and 5 year risk of turmoil in a country, from *Political Risk Services (PRS)*, a provider of international data to businesses and research institutions. The term turmoil refers to, "...large-scale protests, general strikes, demonstrations, riots, terrorism, guerrilla warfare, civil war, and cross-border war. It also includes turmoil caused by a government's reaction to unrest" (Political Risk Services, PRS Online Definitions, www.countrydata.com/polriskrating.html). Political Risk Services rates the risk of turmoil as either LOW, MODERATE, HIGH, or VERY HIGH. These ratings are useful because it is straightforward to translate them into binary and discrete variables for the logit, probit, and ordered probit and logit models. In addition, the criteria that PRS uses to classify a country according to turmoil risk are comparable to the stages of conflict posited by Jongman (1994).

The PRS data is transformed into binary and discrete dependent variables. For the binary dependent variable, a country receives a score of 0 (no risk) if either the 18-month or 5-year PRS turmoil risk rating is LOW. Otherwise, the country receives a score of 1. This dependent variable is employed in the estimation of the logit and probit models. The discrete dependent variable corresponds to the PRS turmoil risk levels as follows: 0 = LOW, 1 = MODERATE, 2 = HIGH, 3 = VERY HIGH. Because the discrete dependent variable has a finer gradient, it includes more information. This additional information should result in a more accurate forecast.

The independent variables are chosen to reflect the level of stress on a nation's environment. Homer-Dixon (1994, p. 6) posits six types of environmental change that are plausible sources of conflict. They are:

1. greenhouse-induced climate change
2. stratospheric ozone depletion
3. degradation and loss of good agricultural land
4. degradation and removal of forests
5. depletion and pollution of fresh water supplies
6. depletion of fisheries

Greenhouse-induced climate change and stratospheric ozone depletion may generate conflict if these problems generate intolerable living conditions in a region. These conditions may induce migration, resulting in conflict between the migrants and the established residents. Data on environmental migration is scattered at best. Therefore, the only variable used to measure these global effects is total CO_2 emissions from industry (CO2), measured in thousands of metric tons. Based on his case studies, Homer-Dixon (1994) argues that global environmental variables are not likely to place a large role in conflicts. Therefore, it is not expected that this variable will have a significant coefficient. Regional environmental conditions, however, may play a much larger role in conflicts. The

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problems of the region surrounding the Aral Sea are a case in point. The role of such variables in conflict points to a need for improved data on regional environmental problems and environmentally induced migration.

Degradation and loss of good agricultural land may generate simple scarcity conflicts as well as group conflicts via environmentally induced migration, both internal and international. The same holds true for deforestation, water pollution, and fishery depletion. As the quality of the land deteriorates and it is less able to support the people who live on it, conflicts over the use of the remaining resources may erupt. Furthermore, as the population living in a region exceeds the carrying capacity, people will have to move on. Conflict may then erupt in the new location over the resources there.

The following variables are used to measure the degradation and loss of good agricultural land (variable names are in parentheses): the 10-year percent change in the index of food production (DFOODP), cropland per capita in hectares (CROPL), irrigated land as a percent of cropland (IRRIG), net trade (imports-exports) in cereals in thousands of metric tons (TCEREAL), net receipts of food aid in thousand of metric tons of cereals (FACEREAL), and domesticated land as a percent of land area (DOMES). Declining per capita food production, and less cropland per capita may indicate a country's inability to feed its people. This inability may generate conflict. Therefore, the coefficients of these variables are expected to be negative. By the same logic, net imports of cereals and net receipts of food aid should have positive coefficients. As domestic land as a percent of land area approaches unity, the country has less room to expand. This may indicate increased probability of conflict, resulting in a positive coefficient. Finally, irrigated land as a percent of cropland may indicate more intensively farmed land. If this is an indication of a higher level of development, the likelihood of conflict may be reduced. Given that irrigation makes crops less susceptible to weather shocks, more irrigated land may also indicate a more certain food supply, reducing tension due to food shortages. However, if more irrigated land indicates a need to get more out of the land and a strain on other resources such as water, the probability of conflict may be increased. Extremely high or extremely low values of these variables may cause problems. For example, Botswana has no irrigated cropland, while 100% of Egypt's cropland is irrigated. Either one of these conditions may signal stress on the system. Therefore, the sign of this variable is unclear.

The 10-year average annual percent change in total forest (FOREST) is used to measure the degradation and removal of forests. A negative value indicates forest loss, which may increase the likelihood of conflict. Therefore, it is expected that this variable will have a negative coefficient.

Annual internal renewable water resources in cubic kilometers (H2ORES), annual river flow from other countries in cubic kilometers (FLOW), and withdrawals as a percent of the total supply (H2OUSE) are used to measure the quanity of water resources. As a country's fresh water supply is larger, its likelihood of conflict should fall. Therefore, this variable should have a negative coefficient. However, as supply that is from other countries or withdrawals as a percent of supply increase, the security of the remaining supply falls, thus increasing the likelihood of conflict. Therefore, these last two variables should have positive coefficients.

The average annual marine and freshwater catches (FISHM and FISHF, respectively) in thousands of metric tons are used to measure fishery resources. Countries with a larger catch may have a larger dependence on fish resources. Therefore, conflict may increase with increased catch. These variables should have positive coefficients.

In addition to the above variables, a number of socioeconomic variables are included in the model to control for the level of development in a country. They are: per capita GDP (PCGDP) in 1993 US$, the percent of GDP from agriculture (AGGDP), official development assistance as a percent of GDP (ODA), the population growth rates for the most recent 5-year period (PG9095 AND PG0005), population density in individuals per 1,000 hectares (PDENS), and commercial energy consumption (ENERG) in petajoules. To the extent that lower per capita GDP, higher percent of GDP from agriculture, higher development assistance, and higher external debt indicate a less developed economy, they may indicate increased pressures on the citizens to provide for themselves and may result in increased incidence of conflict. Therefore, it is expected that per capita GDP will have a negative coefficient, while these other variables will have positive coefficients. The dynamic models of population and renewable resource interaction show that increased pressure from the population on a resource can result in conflict. Therefore, population growth rates and population density are expected to have positive coefficients. Higher commercial energy consumption indicates a higher level of development. Therefore, this variable is expected to have a negative coefficient.

Data from 95 countries from *World Resources, 1996-97* is employed in the estimation of the model. Missing observations are filled in using the mean value of the variable for the surrounding geographic region. All data documentation is available by request from the author. Forecasts are generated for these 95 countries using data from *World Resources, 1998-99*. In addition forecasts are computed for an additional 22 countries for which dependent variable data is not available using both the 1996-97 and 1998-99 *World Resources* data. The values for H2ORES, H2OUSE, and FLOW North, Central, and South American, Asia, and Oceania are missing from the 1998-99 edition of *World Resources*. Therefore, forecasts are generated using the 1996-97 values of these variables. The forecasts will be recomputed using the updated data once it becomes available. Data for PCGDP from the 1998-99 editions of *World Resources* is converted from 1995 to 1993 dollars using the implicit GDP price deflator (*Survey of Current Business*, August 1998).

RESULTS

Initial models are estimated using all variables. However, not surprisingly, carbon dioxide emissions are highly collinear with commercial energy consumption. Their correlation coefficient is 0.98. Therefore, in order to avoid introducing severe multicollinearity into the model, commercial energy consumption is omitted from the final models.

In the interests of space, the results of all model estimations are summarized here without the accompanying tables. A complete set of output tables is available from the author upon request.

The results from the logit and probit models are similar. In both models all variables have the same sign and similar levels of significance. The following variables are significant in both models (p-values from the logit and probit models, respectively, are in parentheses): official development assistance (0.009,0.008), population density (0.046,0.050), the change in the index of food production (0.003,0.002), net trade in cereals (0.039,0.042), net cereal aid receipts (0.018,0.013), percent change in forest area (0.008,0.006), and average annual internal renewable water resources (0.034,0.034). In addition, the change in the index of food production, net trade in cereals, net cereal aid receipts, and the change in forest area all have the expected sign. Official development assistance has a negative coefficient, when it was expected to be positive. This result may indicate that development aid helps to alleviate internal pressures in a country, resulting a reduced likelihood of conflict. Population density also has a negative effect on the probability of conflict, when it was expected to have a positive effect. This result reflects the fact that more developed countries tend to be more densely populated. More developed countries have also had a lower incidence of conflict in recent years. Perhaps the most surprising result is that the coefficient of average annual internal water resources is positive, when the coefficient was expected to be negative. This result indicates that countries with a larger freshwater supply actually have an increased likelihood for conflict. Perhaps this is because countries with larger water supplies tend to be downstream countries. In one sense, then, their water supply is the most threatened. Overlaying this result with GIS information about major river systems of the world might reveal whether the downstream effect is generating this result.

In-sample forecasts for the 95 countries in the original data set were generated to validate the model. Both the logit and probit models correctly forecasted the value of the dependent variable 88% of the time. In addition, out of sample forecasts were generated for 22 countries using the 1996-97 data. Of these countries, the following had high probabilities of conflict (logit and probit probabilities, respectively, follow in parentheses): Afghanistan (1,1), Cambodia (1,1), Eritrea (0.97,0.98), Ethiopia (1,1), and Somalia (1,1). Out of sample forecasts for all 117 countries were generated using the World Resources 1998-99 data. Table 1 at the end of the text reports the countries that have the 5 highest probabilities of conflict. Perhaps the only surprising member of the top 5 is Brazil. This result is most likely driven by Brazil's large annual fresh water supply.

The ordered logit and probit models for 18-month levels of conflict have similar results. Per capita GDP (0.078,0.074), population density (0.027,0.024), the change in the index of food production (0.006,0.007), net cereal food aid receipts (0.040,0.042), change in forest area (0.002,0.003), average annual internal renewable water resources (0.002,0.002), and flow from other countries (0.009,0.008) are all significant, although per capita GDP is only marginally significant. In addition, per capita GDP, the change in the index of agricultural production, net cereal aid receipts, and change in total forest area all have the expected sign. The signs of population density and average annual internal renewable water resources are the same as in the simple logit and probit models. Their effects on level of conflict appear to be the same as in the models above. A surprising result is that the coefficient of the percent of water supply that flows from other countries is negative, when it was expected to be positive. One possible explanation is that countries that receive large percentages of their water supply are more likely to

negotiate solutions to disputes rather than enter into armed conflict. Again, a GIS overlay of river basins accompanied with data about water supplies, flow directions, and amounts would be invaluable in providing insight into this result.

The ordered logit and probit models for 5-year levels of conflict have the following significant variables: per capita GDP ((0.091,0.084), average annual rate of population growth from 2000-05 (0.010,0.007), the change in the index of food production (0.016,0.022), and net imports of cereals (0.098,0.054). All of the coefficients have the expected sign.

In sample predictions are generated for the original 95 countries in the data set. The 18-month ordered logit model correctly forecasts the conflict category 55% of the time, while the 18-month ordered probit model correctly forecasts 60% of the time. The 5-year ordered logit and probit correct prediction rates are 65% and 62%, respectively.

Out of sample predictions are generated for an additional 22 countries using the 1996-97 data. Somalia and Ethiopia are predicted to fall in the VERY HIGH level of conflict category over the 18-month time period. Somalia, Ethiopia, and Brazil are predicted to fall in the VERY HIGH category over the 5-year time period. Out of sample predictions are generated for all 117 countries using the 1998-99 data. A complete set of tables with predicted categories of conflict and probabilities of falling in each category are available upon request from the author. For the 18-month time period, Afghanistan, Russia, and Jamaica are predicted to fall in the VERY HIGH category. This last result is somewhat surprising. An examination of the environmental conditions in Jamaica provides no immediate insight into why it is predicted to experience high levels of conflict. This result does not carry through to the 5-year predictions. Therefore, it may be an anomalous result. Brazil is the only country predicted to fall in the VERY HIGH category over the 5-year time horizon. This result is very likely due to Brazil's large water supply. The apparent importance of this variable points to the need to use a measure that more accurately reflects the stress that is being placed on a nation's water system. One such measure is the hydraulic density of population, which measures the number of persons per million cubic meters of water per year. This number is then transformed to a water scarcity index, which reflects the amount of water stress that a country is experiencing. Typically, developed countries have the capacity to manage a higher level of water stress than developing countries (Myers, 1993). The ratio of the hydraulic density of population to its water stress threshold level would be a better measure of the pressure on a region's water supply. Future studies will attempt to incorporate this information.

Conclusions and Recommendations for Future Research

These preliminary results indicate that environmental variables do have some power in predicting the potential for conflict. Such variables as water and food supplies and deforestation do appear to indicate potential locations of future conflicts. However, if accurate forecasts of conflict as a result of environmental scarcity are to be made, better data is needed. The data from case studies is simply not varied enough with respect to the dependent or independent variables to be useful for forecasting. Furthermore, much of the aggregate data does not measure exactly the variables that may be useful in predicting conflict. One new technology that promises to be very useful in accumulating environment and conflict data is the Geographic Information System (GIS). Such a system includes a map with geographic characteristics. In addition, characteristics about a region such as per capita GDP are linked to each region and are available at the click of a button. There is no limit to the amount or type of information that can be linked to a given geographic area. All of this information can then be downloaded in spreadsheet form to a statistical software package for analysis. Nils Petter Gleditsch (1998) states that rigorous research in this area requires a "Correlates of War for the environment" (p. 396). If such a data collection project is undertaken, GIS is an obvious format for the data.

Homer-Dixon (1994) states that many environmental conflicts will occur at the subnational level. If this is the case, then regional level data is necessary to forecast such conflicts. Environmental conditions vary greatly across large countries like Brazil and Russia. It is very difficult to make forecasts from data that are averaged across regions that have a great deal of geographic variation. For one thing, much of the useful variation in the data is lost when it is averaged by looking at variables at the national level only. The need for such regional information points again to the need for the use of a GIS system for data collection.

Lastly, the theory on the interaction between population and the environment indicates that the relationship is dynamic in nature. Therefore, it is more appropriate to use a panel data or simultaneous equation model to model these dynamic effects than the static cross-sectional model presented here. Again, there is very little data available for this type of modeling at this time.

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There is another approach to modeling the interaction between the population, the environment, and conflict that may be useful in determining which variables are key in generating conflict. Computable general equilibrium simulations essentially model small economies. They can be easily modified to include environmental variables. The potential for using such models to examine when environmental conditions generate conflict should be investigated.

Clearly, a Correlates of War project for the environment is called for if we are to seriously investigate the relationship between conflict and the environment. This study is an attempt to examine the issue in the best way possible given the available data. Although, the preliminary evidence indicates that environmental variables are predictive of conflict, this study has barely scraped an ice crystal off the tip of the iceberg. The initial statistical and case study research has gone nearly as far as it can go given the available data. Future research should focus on accumulating more basic data so that future forecasters may benefit.

TABLE 1. TOP 5 FORECASTED PROBABILITIES OF CONFLICT – LOGIT AND PROBIT MODELS

Logit Model	Probit Model
Russia	Russia
Brazil	Afghanistan
Afghanistan	Bangladesh
Bangladesh	Myanmar
Indonesia	Ethiopia

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I. S. O. PREDICTION YARDSTICKS VIA DYNAMIC PROGRAMMING

by Elliot Levy

Introduction

The dynamic programming technique was introduced by Richard Bellman of Rand Corporation for **reducing the number of independent variables** in multi-stage processes[1], as in manufacturing operations. The objective was to obtain a solution for the optimal state in succeeding stages of a process, specified mathematically by a maximization equation, incorporating the objective function that also includes the maximization of a remainder left from the activity of every previous stage. Also, the behavior of the variables act as limits or constraints for the solution. Generally, this maximization algorithm has the following notation:

Maximum Return Objective Function

$$\underset{n+1}{\text{Max } R(x)} = \text{Max } [\ F(x) + r(x)\ ],$$

where r = remainder

Subject to: Constraints

$$1 \leq x \geq 5$$
$$i \quad \} \text{ variable behavior}$$
$$i = 1, \ldots, 20$$

The maximum of the next stage equals what was maximized previously plus the optimal result for the remainder of the next stage.

This objective function is a transformation mapping of each succeeding to final stage[2], expressed mathematically as a transformation function of :

$$\underset{n+1}{\text{Max } (R)} = \text{Max } | T \quad (x, r)|$$

In order to have maximum solutions per stage, r = remainder, also must be optimal outcome in tandem for all stages.

The cumbersome mathematical details are found in the various papers of Bellman and others. The previous mathematical descriptions were made simple in order focus on this programming technique as a forecasting utility instead of addressing equation art deja vu.

Prototype Application

This programming method, a tool of Operations Research for maximum-minimum solutions, has been applied here to an on-site vendor situation where a private company allows these vendors on their premises to sell items that satisfy personal needs of employees, such as jewelry, coupon books, apparel articles requiring no measurements, fragrances, small household items, plants, etc. Nearly, all of these products are cash and carry , which is the policy set by the company employee welfare association. The sales process appears in the form of a flow chart in **Figure 1**. By applying a Dynamic programming solution to find vendor sales maximization capability, this company recreation association was able to denote some vendors actually maximizing sales, as **optimal states**, for the years or **stages** of on-site operation. To be of greater service to employees, the company welfare association's board of officers had been interested an employee store on the premises. From the maximum sales of specific vendors, an inventory of selected items can possibly be structured. Currently, the employee association collects a fixed percent per vendor as a commission which will be used as the data in the dynamic programming solution. The data matrix contains commissions from eighteen types of vendors annually for fifteen years.

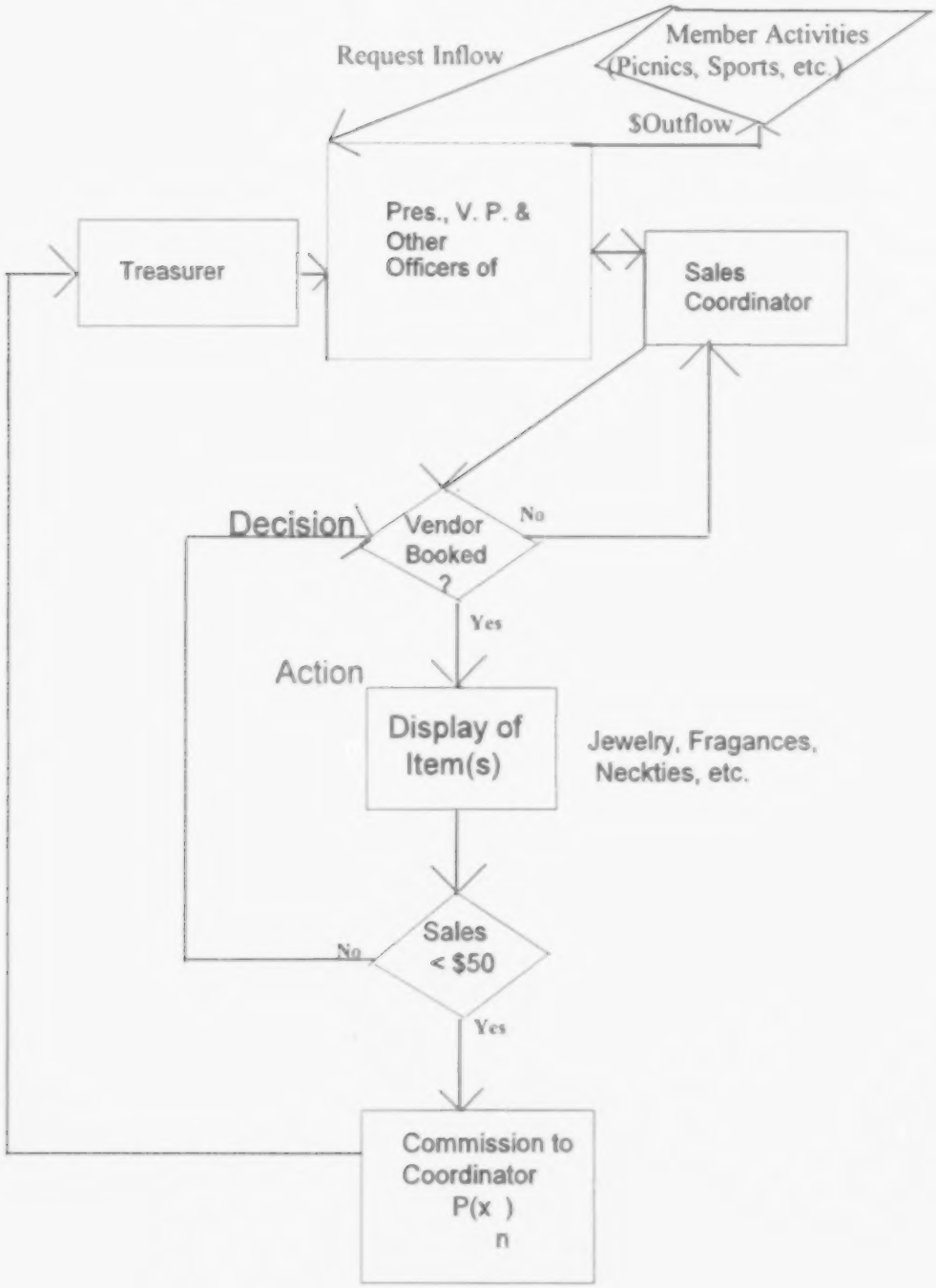
The On-site Vendor Maximization rules are mathematically postulated as follows:

Maximum % Return Objective Function

$$\underset{n+1}{\text{Max } P} \quad (x) = \text{Max } [p(x) + f^{*} \quad (s - x \quad)\ ],$$

where **p(x)** , the **commissions** and **f *(s-x)**, the **remainder** are **to be maximized -per vendor-in** state **(s)** by each stage of vendors, **x , n=1 to 15** years.

Figure 1. Flow Chart of On-Site Sales



The computation process is recursive, moving backwards from final to initial stage, years 1997 to 1983. The maximum percent in each year has been added to the previous years commissions per vendor in order to obtain their optimal state throughout every backward stage of the fifteen year trend. This is similar to the insurance salesman problem, where the salesman derives the optimal route from the past ones taken. [3] Thus, this dynamic programming computation method is a backwards additive optimal procedure, because it aggregates maximum to past optimum percent. By working backwards, it uses the actual past data instead of a forward procedure that requires projections the unknown.

The purpose for suggesting dynamic programming was that there were eighteen states of different vendors for the fifteen year stages and if the policy of the welfare association were a store, it would primarily predicated on the composition of best vendor sales, and thus, this information took on the following priority:

1. If there were several kinds of vendors in the optimal mix, then a store would be feasible.
2. If there were only a few prominent ones, say three, then the on-site selling at a given location would be more pragmatic.

Application Formulae

The vendor dynamic programming problem applies the following algebraic notation [4]:

Notation:

1. $p(x_n)_n$ = Current vendor commissions as percent of total annual commissions, years 1983-1997.
2. $f(s-x_n)_n$ = Sum of (1) the current percent plus the (2) optimum percentages of previous iteration(s) or stage(s), involving 1 and 2. The sum of these two quantities becomes an individual cell value in a matrix of like input to compute maximum value(s) used in the next iteration.
3. $f^*(s-x_n)_n$ = Maximum cell value, of these percentages which are cumulative sums of vendor commissions as the remainder which is input generated for the next iteration.

The objective function is:

$$\text{Maximize}: [p(x_n)_n] = f_n(s, x_n)_n = p_n(x_n)_n + f^*_{n+1}(s-x_n)_n$$

Subject to: x_n, n stages of vendors (n = 1, ..., 15).

The objective is to maximize cumulative commissions, in a backwards process, within the confines or resource limits of the eighteen vendors as independent variables. Thus, this maximum is determined from the past performance- the known commissions of these vendors-which would be the constraint limits or borders of geometric mapping of the problem.

Mapping formulas for dynamic programming stem from optimization theory mathematics. In a map for an area D there are n sets of transformations of an optimization plan p, with p comprising a vector. [5]

Expressing it, mathematically as:

$$T(p)_1 = p_1, \ldots, p_k = T(p)_n = p_n,$$

for k stages involving n states.

By connecting either a column or row vector of vendor solutions,

$$T_1(p_1) = f_1(s_1), \ldots, T_n(p_n) = f_n(s_n).$$

The maximum $f_k(s_k)$, $f^*(s)$, is determined from all of the $f(s_k)$, k= 1,...,n.

$$\text{Max } T(p) = \text{Max } f(s) = f^*(s).$$

Incorporating the formula for vendor maximization,

$$f^*(s) = \{\max [p_i x_i + f^*(s - x_i)_j]\},$$

where

i = (1, ..., n) states

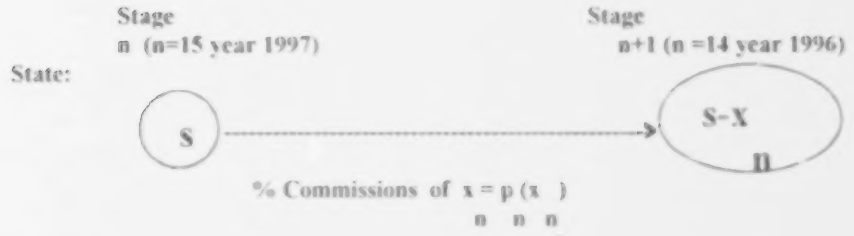
and

j = (1, ..., k) stages.

Also, using the sup norm metric to show a maximum will be reached. [6]

$$f^*(s) = \sup [p_i x_i + f^*(s - x_i)_j]$$

Figure 2. DIAGRAM OF VENDOR PROBLEM STRUCTURE



Accumulated Maximum Values from consecutive % Commission through the last stage(s)

Accumulated Optimum Values with p (x) contribution going toward maximization of the next past stage
n n

$$f(s, x_n) = p(x_n, n) + f^*_{n+1}(s - x_n)$$

The sup norm metric shows a convergence condition at the maximum, where each feasible policy, f(s), of the p vectors will approach f*(s), the optimal policy. I have touched on the algebraic tools just to expose a few concepts. Please consult the **references** for the intricate detail.

The diagram of this vendor problem, as presented in **Figure2**, as a recursive process , where an optimal state in n+1 is applied toward the optimal state in n [7]. Thus the process has its direction reversed in this 1983-97 time span, throughout 15 annual stages, backwards beginning with each vendor's commission for 1997, which is stage 15, the beginning year, **(n+1)**.

As depicted, the process moves in reverse direction of final to initial year, as if going backwards in time. Every vendor provides a maximum percent value f* per stage, which is cumulative sum of percent in the **current year (n)** added to a maximum value of the **next year(n+1)**. Percent accumulations-as whole numbers-continue up through the earliest year (1983), the last iteration in the calculation where the **final cumulative maximum is derived at stage n=1**. Thus, this process traces back the various yearly stages in search of a vendor's maximum commission. As this procedure typifies that of a traveling salesman looking for the most optimal route from those previously taken. This computation, backwards additive, aggregated maximums of vendor commissions, from current to prior year. Projections are not required because this procedure is not extending beyond the current stage, but moving backwards, in time, dictated by actual past performance. Thus, a deterministic dynamic programming method has been applied in order to process these vendor percentages toward their optimum.

Solution of the Vendor Problem

Details of the solution are found in **Tables I and II, following the text**. A solution to this dynamic programming problem was obtained in using the data input of Table I. Vendor Commissions from Employee Sales on Premises . This solution commences with the last year 1997, stage(n = 15), and continues in a backwards direction to 1983, stage (n = 1). This first step of this solution is presented in **Table 1.**

Table 1. OPTIMAL COMMISSION VALUES AND STATES, LAST STAGE(N = 15)

Commodity Vended	State(s)	f * (s) 15	x * 15
Jewelry	0	20	0
Clothes	1	30	1
Plants	2	3	2
Food(Pastry, etc.)	3	0	3
Art	4	0	4
Coupon Books	5	9	5
Variety	6	8	6
Company Almanac	7	0	7
Perfumes & Fragrances	8	0	8
Brass	9	0	9
Other Commodities	10	0	10
Computer Software	11	0	11
Books for Reading	12	6	12
Cellular Phones	13	6	13
Music - Tapes & Compact Disks	14	10	14
Dolls & Figurines	15	4	15
Gift Baskets	16	3	16
Household Items	17	0	17

In the remainder of this paper, the author will discuss the facets of computation and interpretation of results, without intruding upon the particulars related to confidential disclosure of the data source.

The f* values are the % vendor commissions-assumed to be optimal for 1997in Table I. The eighteen vendors which are the states per stage are coded as 0,...,17. This dynamic programming structure is an [s by n] matrix, where there are s = 18 vendors or states and n =15 years or stages. The * denotes optimal vendor (x *) corresponding to their cumulative % commissions that incorporates remaining optimums from accumulated % commissions, $f^*_{n+1}(s,x)$, per nth stage.

In the beginning stage, shown above, the percent from each vendor was considered optimal.[9]. The method presented was (1) additive, and (2) in this particular situation the vendor % commissions, were treated as whole numbers to avoid decimal places to make processing the data easier.

In the next iteration for (stage n=14) or year 1996, an 18 X 18 matrix had been created from two vectors, the 1997 maximum **f *'s** and the 1996 **px's** as current commission data. By adding 1997 data to each data element in 1996, a squared matrix was created, with s down and (s-x) across. Diagonal values by (s-x) made all columns positively indexed, each column starting one element down from the previous column, preventing negatively assigned column references. Diagonals shown in 1996, in **Table 2**, incorporate positively indexed values when $x \leq s$.

Table 2. DIAGONAL VALUES FOR YEAR 1996, STAGE N = 14

Commodity	State =	Diagonal: Location	$f(s, x) = p(x) + f^*(0)$ $14\ 14\ \ 14\ 14\ \ 15$		
Jewelry	0	s_{0}, x_{0}	33	13	20
Clothes	1	s_{1}, x_{1}	38	18	20
Plants	2	s_{2}, x_{2}	29	9	20
Food (Pastry, etc.)	3	s_{3}, x_{3}	22	2	20
Art	4	s_{4}, x_{4}	20	0	20
Coupon Books	5	s_{5}, x_{5}	30	10	20
Variety	6	s_{6}, x_{6}	23	3	20
Company Almanac	7	s_{7}, x_{7}	20	0	20
Perfumes & Fragrances	8	s_{8}, x_{8}	21	1	20
Brass	9	s_{9}, x_{9}	20	0	20
Other Commodities	10	s_{10}, x_{10}	20	0	20
Computer Software	11	s_{11}, x_{11}	22	2	20
Books for Reading	12	s_{12}, x_{12}	43	23	20
Cellular Phones	13	s_{13}, x_{13}	38	18	20
Music - Tapes & Compact Disks	14	s_{14}, x_{14}	20	0	20
Dolls & Figurines	15	s_{15}, x_{15}	20	0	20
Gift Baskets	16	s_{16}, x_{16}	20	0	20
Household Items	17	s_{17}, x_{17}	20	0	20

Note : Each diagonal value is the first element per row when f* is indexed at zero.

This computation cycle commenced with constructing a square matrix for 1996. Only diagonal calculations were presented. In the diagonal example percent values for every vendor in year 1996 $[p_{14}(x_{14})]$ were varied against a constant maximum percent $[f^*_{15}(0)]$ To calculate **columns** of the elements, the process is reversed, because the annual percent values are the constants added to these maximum values, $f^*_{n+1}(s)$.

Again, the added maximum is an aggregative sum, continuing absorbed in iterations to (**n = 1**) year 1983.

In **Table 3**, the computations for columns 1 and 2 in **n = 14** (Year 1996) are shown by the cumulative process of adjoining the 1996 % commissions data with the maximum values of **n=15**.

Table3. Column Computation

Column 1			Column 2		
1996 % data	+ max. n=15	= 1st Column	1996 % data	+ max. n=15	= 2nd Column
13	20	33			blank
13	30	43	18	20	38
13	3	16	18	30	48
13	0	13	18	3	21
13	0	13	18	0	18
13	9	22	18	0	18
13	8	21	18	9	27
13	0	13	18	8	26
13	0	13	18	0	18
13	0	13	18	0	18
13	0	13	18	0	18
13	0	13	18	0	18
13	6	19	18	0	18
13	6	19	18	6	24
13	10	23	18	6	24
13	4	17	18	10	28
13	3	16	18	4	22
13	0	13	18	3	21

Table 4. Vector and Matrix Arrangements Per Stage

Stage	Year	Computation Procedure
n=15	1997	Vector
n=14	1996	Matrix
n=13	1995	Matrix
n=12	1994	Matrix
n=11	1993	Matrix
n=10	1992	Matrix
n= 9	1991	Matrix
n= 8	1990	Matrix
n= 7	1989	Matrix
n= 6	1988	Matrix
n= 5	1987	Matrix
n= 4	1986	Matrix
n= 3	1985	Matrix
n= 2	1984	Matrix
n= 1	1983	Vector

As shown in **Table 3**, each succeeding column starts one element below the previous column. As a result of this procedure, the maximum values, that are added to each column constant value, were descending consecutively one column position per column, e.g. zero is the bottom value of **Column 1** maximums (n=15) and 3 is now the bottom value in that of **Column 2**, where the entire row vector has shifted one position down.

The matrices for 1996 and 1995 are presented in Table II at the end of the text.

This computation process involved construction of matrices from two columns of data within two vectors, expanding one vector at the start and contracting one matrix at the end of the solution. This last vector contained the maximum accumulation of vendor commissions including the state(location) where this maximum was found.

Vector and matrix arrangements for all stages of vendor optimal calculations is shown in **Table 4**

Figure 3. Final Stage of the Solution (n = 1)

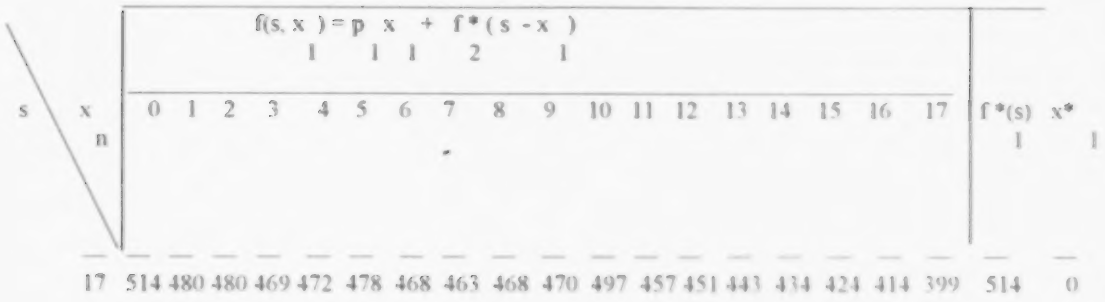


Table 5. APPLICATION OF DYNAMIC PROGRAMMING RESULTS

Stage	(s) Optimal Vendor State	Corresponding x* value n	n+1= (s-x*) n	Vendor	Year
n= 1	17	0	17	Jewelry	1983
n= 2	17	0	17	Jewelry	1984
n= 3	17	0	17	Jewelry	1985
n= 4	17	0	17	Jewelry	1986
n= 5	17	0	17	Jewelry	1987
n= 6	17	0	17	Jewelry	1988
n= 7	17	1	16	Clothes	1989
n= 8	16	0	16	Jewelry	1990
n= 9	16	1	15	Clothes	1991
n=10	15	1	14	Clothes	1992
n=11	14	1	13	Clothes	1993
n=12	13	1	12	Clothes	1994
n=13	12	11	1	Software	1995
n=14	1	0	1	Jewelry	1996
n=15	1	1	0	Clothes	1997

Summary for x * Optimal Vendor State:

$[x_n]$ = (0,0,0,0,0,0,1,0,1,1,1,1,11,0,1] (n=0,..,15) Solution

15[x n] = 8[x 0] + 6 [x 1] + x 11 {0=Jewelry, 1=Clothes, 11= Software}

The final stage in **Figure 3** contains maximum % accumulated commissions from adding the **1984 f*(s)** maximums by an $(s - x_n)$ index to reverse their order before adding them to each 1983 percent for the completion of the solution, that was started from data as percentages made into whole numbers.

Table 6. Years of Highest Commission from Optimal Vendors

Vended item	# Optimal Years	Optimal Years
1. Jewelry	8	1983-88, 1990, 1996
2. Clothes	6	1989, 1991-4, 1997
3. Software	1	1995
Total:	15	

Table 7. OPTIMAL VENDORS FROM FOUR DYNAMIC PROGRAMMING MODELS

Progamming Model	Optimal Vendors
1. **Additive**	***Jewelry, Clothes**, and Software
2. **Average**	**Jewelry, Clothes,** and Other
3. **Multiplicative**	**Jewelry,** Clothes, Software , and Coupon Books
4. **Median or Splice**	**Jewelry, Clothes,** and Other

*** Bold letters indicate optimal vendors in most stages.**

This **final maximum** value and its **location**, shown in the last two columns for stage n=1, in **Figure 3,** had provided starting points for searching each of the previous fourteen stages for the optimal state per stage to locate the vendor(s) providing the highest returns to the company recreation association.

Application of the Programming Solution:

By applying this programming solution, the best states of vendor types were found for every stage . In order to find these optimal states, it required starting from stage **n=1(1983 Matrix)** and working forward to stage **n=15(1997 Matrix)**. The **optimal** vendor per state was determined by **x*** , **optimal location** among vendors ranging from **(0,..,17)** and then **deducting** that value from **(s-x*) remaining locations** in order to compute the other optimal locations in tandem. These **optimal states** with their **locations** were shown in **Table 5**.

Also, the **mathematical** and **verbal summaries(bottom Table5 & Table 6.)** present the years where these top vendors had provided the highest commissions to the company's recreation association.

In **Table I(B)**, succeeding the text, **Commission from Three Dominant Vendor's**, showed that there was an agreement between history and solution in the optimal states for the fifteen stages of vendor operations . This table had depicted that this company's welfare association has scheduled jewelry and clothing merchants combined from 1984-97, even amidst the software surge in 1994-5. In 1998- **beyond the data range**, there was **the same outcome,** if one were to **forecast one-year ahead.** Miscellaneous merchants were not included in this table, such as sellers of variety items, also having jewelry and clothes. They gave commissions in fragments, as inconsistent providers toward the fund raising effort of the association. These fragmentary commissions were from Art, Plants, and Food merchants. However in 1993, Coupon Book and merchandise vendors, other than those of jewelry and clothing, gave much larger commissions than usual, 1/4 and 1/3 of recreation association's annual sales, respectively.

Other dynamic programming models were used, e.g. (1)Average of Maximum Annual Percent Commission by Vendor and (2) Multiplicative Percent Annual Commission per Vendor, which had smaller size numerical content. However, their results, as shown in **Table 7**, were approximately the same.

The results show that there were only five vendors that were prominent in selling items on company premises. It would appear that it would be best to forego an employee store and try a better location. Generally, these results show that a paucity vendors have largest bulk of the sales and possibly more sales in greater variety may result from **changing the on-site location** coupled with vendor sales announced in a newsletter, to provide them with **greater visibility** in order to succumb the heterogeneity.

Table 8. CORRELATION COEFFICIENTS OF OPTIMAL STATES, BY D.D.P. MODEL

Iteration	Stage n vs. Stage n-1	MODEL: Additive	Average	Percent
1	n=15 vs. n=14	0.44	0.34	0.40
2	n=14 vs. n=13	0.19	0.17	0.68
3	n=13 vs. n=12	0.71	0.85	0.84
4	n=12 vs. n=11	0.86	0.83	0.72
5	n=11 vs. n=10	0.91	0.69	Not. Determ.
6	n=10 vs. n= 9	0.94	1 .00	No Regr.
7	n= 9 vs. n= 8	1.00	Not. Determ.	No Regr.
8	n= 8 vs. n= 7	0.95	No Regr.	No Regr.
9	n= 7 vs. n= 6	1.00	No Regr.	No Regr.
10	n= 6 vs. n= 5	1.00	No Regr.	No Regr.
11	n= 5 vs. n= 4	0.99	No Regr.	No Regr.
12	n= 4 vs. n= 3	1.00	No Regr.	No Regr.
13	n= 3 vs. n= 2	0.76	No Regr.	No Regr.

1. D. D. P. = Deterministic Dynamic Programming
2. Not Determ.= Regression was not able to compute Coefficient of Determination.
3. No Regr.= No regression, because data had no variance.
   Regression unable to invert matrix, because of singularity.
4. There is no column, only a single value for stage n=1.

Finding the optimal vendor by maximum commission is a **micro**-dynamic programming example. A **macro**-situation is a country determining the highest commodity import duties state(s) from stages in foreign trade.

Intercorrelation Experience

Correlation coefficients above 0.90 were found between many of the optimal states in various consecutive stages. Intercorrelated states are extra dimensionality, indicating certain vendors as superfluous in this particular on-site selling operation. In manufacturing , intercorrelation denotes bottlenecks in the production process.[10] From the results appearing below in **Table 8**, the least prominent vendor categories encumbered this fund raising effort of the employee association, which implied that their board of directors should survey what vendors are demanded by employees of the company.

The results from the **Optimal State Correlation Coefficients** in **Table III** following the text, present this intercorrelation happenstance. Also, these correlation outcomes limits to the number of viable stages per type of model. In the average model, the optimal converged to a constant value for all eighteen vendors after seven and in the percent model after five **stage iterations**. In spite of these limitations, **all models displayed similar parsimony** in vendor selection **to predict the commission outcomes of vendors** in the welfare association fund raising effort .

Summary and Conclusion

The dynamic programming technique - developed from a transformed maximization algorithm was the analytical tool applied for determining what vendors were maximizing commissions, as a part of a recreation association's fund raising activities. The performance of these vendors were independent variables for the objective of solving for those merchants that were optimal as predictors of the association's proceeds as the money needed to generate various activiites for their membership. This particular problem was employed as a prototype situation for demonstrating the technique. A fifteen year time span, 1983-97covered the annual **stages** of vendor sales of personal use items to employees of a business establishment. Also, the **states** were the various vendor sales, e.g. jewelry.

The dynamic programming method is a tool of Operations Research for finding the maximum state(s) within many stages of operation, such as in manufacturing. It appeared that this vendor situation required a dynamic programming solution as a problem with states and stages, not in the depth of manufacturing.

This dynamic programming problem was stated verbally as follows:

1. Objective Function: Find individual vendors **(states)** that have maximized percent of sales commissions for the recreation association from eighteen on site sellers per year **(stages)** from 1983-97.

2. Subject to: The **sales performance of these vendors(independent variables)**.

This dynamic programming computation process is a **recursive process** that started with stage n = 15 **(1997)** and iterating backwards in time until stage n=1 **(1983)**. Maximums of accumulated percent commissions coded as whole numbers were **input per consecutive year in reverse order until the final maximum was obtained, typifying a traveling salesman finding the most optimal route** from those taken . The first backward stage (n=15) - a column vector of percent sales data- initiated a chain of successive square matrices of computed maximum cumulative percentages per vendor up to the stage of n=2. The vector calculations from this stage were input into n=1 to obtain the largest maximum of accumulated percentages.

The results showed that most of the maximum vendor states were: (1) jewelry and (2) small personal clothing merchants-ties, scarves, and belts. Jewelry for eight years, clothing for six years, and software for one year were the highest vended items. Also, in the transforming of vendor data ,e.g. annual averages of maximum percent of sales per vendor, about the same results had occurred, few and mostly in the above two categories. The other non-prominent vendors appeared as residual dimensions of this welfare association sales program. These results implied that a reasonable company **policy** is to drop the store idea and locate an other site on the premises **for these vendors to get more visibility** so as to stimulate sales in the other, as well as in those prominent two categories.

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Table I. VENDOR COMMISSIONS (In Percent)FROM SALES TO EMPLOYEES ON PREMISES

A. PERCENT COMMISSION FROM ALL VENDORS

	1983	1984	1985	1986	1987	1988	1989	1990	199	1992	1993	1994	1995	1996	1997
Jewelry	27	56	37	24	38	44	18	44	35	24	24	9	13	13	20
Clothing		1	2	20	13	13	33	22	42	34	32	16	22	18	30
Plants	7	12	4	9	10						2	12	9	9	3
Food	4		7				2				4	9	6	2	
Art	4	4	8	2	6	2	18		3			2			9
Coupon Books	15	5	8	22	8	8	6	19	14	20	25	7	4	10	8
Variety	9	4	15	4	15			1	1	5	6	1	1	3	
Company Almanac					1										
Perfumes/Fragrances	2	1		2				5	2	1				1	
Brass			6	11		3	2	1							
Other *	32	18	11	6	9	30	21	9	4	16	8	9	1	2	
Software												30	44	23	6
Books												5		18	6
Cellular Phones															10
Music -Tapes & Compact Disks															4
Dolls & Figurines															
Gift Baskets															
Household Items															
Total:	100	101	98	100	100	100	100	101	101	100	101	100	100	99	99

B. PERCENT COMMISSION FROM THREE DOMINANT VENDORS

Vended Commodity	1983	1984	1985	1986	1987	1988	1989	1990	199	1992	1993	1994	1995	1996	1997
Jewelry	27	56	37	24	38	44	18	44	35	34	24	9	13	13	20
Clothes		1	2	20	13	13	33	22	42	34	32	16	22	18	30
Software												30	44	2	
Total:	27	57	39	44	51	57	51	66	77	68	56	55	79	33	50

Note: In 1998, Jewelry and Clothes, also had the highest % commission to the company employee welfare association, 31 % and 22 %, respectively.

*Other consists of vendors of photography, personalized story books, towels, piano rental, and bedding. These vendors were providing small commissions or made one time appearances and that is why they were lumped into one miscellaneous category.

1. In Table A., because some percents were rounded, their totals in were not forced to equal 100.

2. Source of data is confidential.

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Table II. ON-SITE VENDOR DYNAMMIC PROGRAMMING PROBLEM

1996 MATRIX : $f(s,x) = p(x) + f^*(s-x)$
$f(14,14) = p(14,14) + f^*(15,14)$

$f^*(15,14)$	$p(x)$ 14 1	s \ x	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	f^* 1	x^* 14
20	13	0	33																		33	0
30	18	1	43	38																	43	0
3	9	2	16	48	29																48	1
0	2	3	13	21	39	22															39	2
0	0	4	13	18	12	32	20														32	3
9	10	5	22	18	9	5	30	30													30	4,5
8	3	6	21	27	9	2	3	40	23												40	5
0	0	7	13	26	18	2	0	13	33	20											33	6
0	1	8	13	18	17	11	0	10	6	30	21										30	7
0	0	9	13	18	9	10	9	10	3	3	31	20									31	8
0	0	10	13	18	9	2	8	19	3	0	4	30	20								30	9
0	2	11	13	18	9	2	0	18	12	0	1	3	30	22							30	10
6	23	12	19	18	9	2	0	10	11	9	1	0	3	32	43						43	12
6	18	13	19	24	9	2	0	10	3	8	10	0	0	5	53	38					53	12
10	0	14	23	24	15	2	0	10	3	0	9	9	0	2	26	48	20				48	13
4	0	15	17	28	15	8	0	10	3	0	1	8	9	2	23	21	30	20			30	14
3	0	16	16	22	19	8	6	10	3	0	1	0	8	11	23	18	3	30	20		30	15
0	0	17	13	21	13	12	6	16	3	0	1	0	0	10	32	18	0	3	30	20	32	12

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1995 MATRIX : $f(s,x) = p(x) + f^*(s-x)$
$f(13,13) = p(13,13) + f^*(14,13)$

$f^*(14,13)$	$p(x)$ 13 13	s \ x	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	f^* 1	x^* 13
33	13	0	46																		46	0
43	22	1	56	55																	56	0
48	9	2	61	65	42																65	1
39	6	3	52	70	52	39															70	1
32	0	4	45	61	57	49	33														61	1
30	4	5	43	54	48	54	43	37													54	1,3
40	1	6	53	52	41	45	48	47	34												53	0
33	0	7	46	62	39	38	39	52	44	33											62	1
30	0	8	43	55	49	36	32	43	49	43	33										55	1
31	0	9	44	52	42	46	30	36	40	48	43	33									52	1
30	1	10	43	53	39	39	40	34	33	39	48	43	34								53	1
30	0	11	43	52	40	36	33	44	31	32	39	48	44	77							77	11
43	0	12	56	52	39	37	30	37	41	30	32	39	49	87	33						87	11
53	44	13	66	65	39	36	31	34	34	40	30	32	40	92	43	33					92	11
48	0	14	61	75	52	36	30	35	31	33	40	30	33	83	48	43	33				83	11
30	0	15	43	70	62	49	30	34	32	30	33	40	31	76	39	48	43	33			76	11
30	0	16	43	52	57	59	43	34	31	31	30	33	41	74	32	39	48	43	33		74	11
32	0	17	45	52	39	54	53	47	31	30	31	30	34	84	30	32	39	48	43	33	84	11

Source for Computation Method:
Frederick S. Hillier and Gerald J. Lieberman, Introduction to Operations (Oakland, CA: Holden-Day, Inc., 1980), pp. 273-5.

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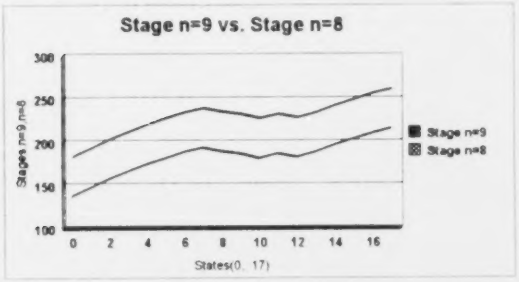
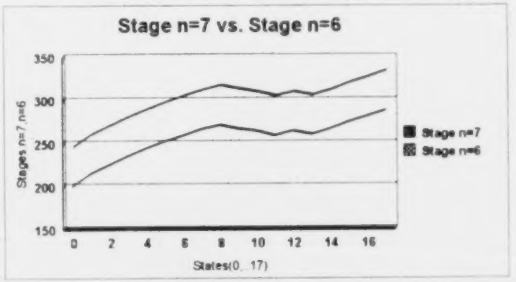
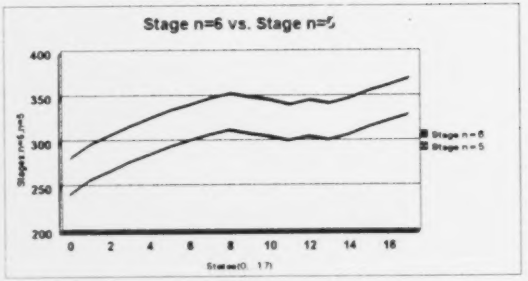
Table III. CORRELATION OF DEMANDS OF OPTIMAL STATES BY CONSECUTIVE STAGE

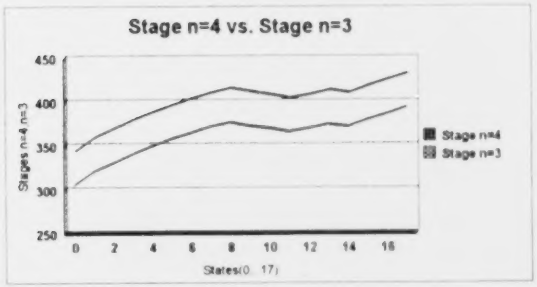
ADDITIVE DETERMINISTIC MODEL (States = s = (0,...,18); Stages = n = (0,...,15))

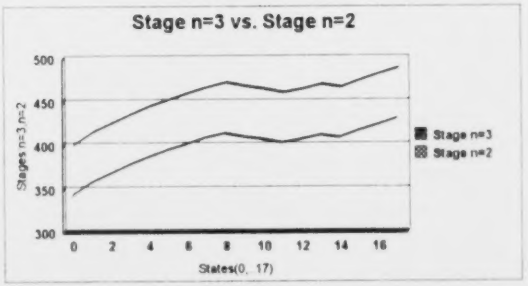
s	(n=15)	(n=14)	(n=13)	(n=12)	(n=11)	(n=10)	(n=9)	(n=8)	(n=7)	(n=6)	(n=5)	(n=4)	(n=3)	(n=2)	(n=1)
0	20	33	46	55	79	103	138	182	200	244	282	306	343	399	514
1	30	43	56	65	89	113	148	192	215	259	297	321	358	414	
2	3	48	65	74	98	123	158	202	225	269	307	331	368	424	
3	0	39	70	81	106	132	167	211	235	279	317	341	378	434	
4	0	32	61	86	113	140	175	219	244	288	326	350	387	443	
5	9	30	54	82	118	147	182	226	252	296	334	358	395	451	
6	8	40	53	79	114	152	189	233	259	303	341	365	402	458	
7	0	33	62	72	111	148	194	238	266	310	348	372	409	465	
8	0	30	55	78	106	145	190	234	271	315	353	377	414	470	
9	0	31	52	74	111	140	187	231	267	311	349	373	410	466	
10	0	30	53	71	107	145	182	226	264	308	346	370	407	463	
11	0	30	77	86	110	141	187	231	259	303	341	366	403	459	
12	6	43	87	96	120	144	183	227	264	308	346	370	407	463	
13	6	53	92	103	128	154	189	233	260	304	342	375	412	468	
14	10	48	83	108	135	162	197	241	266	310	348	372	409	465	
15	4	30	76	104	140	169	204	248	274	318	356	380	417	473	
16	3	30	74	101	136	174	211	255	281	325	363	387	424	480	
17	0	32	84	94	133	170	216	260	288	332	370	394	431	487	
Coeff. of Simple Determination:		0.1104	0.1917	0.7123	0.8640	0.9147	0.9448	1.0000	0.9511	1.0000	1.0000	0.9917	1.0000	1.0000	
Simple Correlation:		0.44	0.19	0.71	0.86	0.91	0.94	1.00	0.95	1.00	1.00	0.99	1.00	1.00	











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PREDICTING ENVIRONMENTAL SECURITY IN AFRICA: A PROTO-TYPE MONITORING SYSTEM OF ENVIRONMENTAL AND SECURITY PROBLEMS IN SOUTHERN AFRICA [1]

by
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Introduction

This paper describes a proto-type system designed to monitor "environmental security" threats in Southern Africa. This system is based on a problem solving theoretical perspective of politics (Purkitt, 1998, Dyson and Purkitt, 1990). When implemented this system will include summaries of relevant research findings; data on current issues and trends relevant to environmental and political issues at the local, national, and regional level; and expert predictions about future environmental problems that may cause political problems. These data are organized in a web-based series of linked home pages organized around the major environmental problem areas of: biodiversity; climate; desertification and deforestation, oceans and fisheries, fresh water, and population trends. These problem areas were selected because they are frequently mentioned in the literature as ones that are likely to contribute to future political instability.

Elite interviews and think-aloud protocols were used to collect perceptual data and subjective judgments about future possible links among environmental variables, population change, and political problems. Analytical techniques developed for other research applications were modified and used in this system to summarize how different political actors represent or frame political problems and possible solutions. These techniques are intended to be used in conjunction with statistical modeling efforts and qualitative case studies.

The data collection methods and analytical techniques used to summarize these interviewees were found to be useful aids for several analytical tasks including: identifying and rank-ordering "environmental security " policy issues in a particular region; identifying alternative definitions of problems and preferred policy solutions to specific environmental-political issues by key actors; constructing future possible conflict scenarios, and as a mechanism for locating new web-based data sources. Although this proto-type system was developed to monitor trends in Southern Africa, the theoretical rationale and methodology can be applied to any region of the world.

The emphasis on perceptual data and subjective judgments was necessitated by the lack of adequate statistical data series at the regional and national level. The emphasis on subjective data also reflects the underlying theoretical perspective that assumes that accurate analysis and predictions about future environmental-political linkages require an understanding of how key political actors define or frame environmental security issues. As we learn more about how people develop shared problem representations of "ill-structured problems" such as how future environmental events and trends are linked to political trends, we should be better able to generate more accurate forecasts.

Past Research Results

A renewed interest in understanding how environmental degradation, resource scarcity, and population growth relate to political conflicts since the end of the Cold War has stimulated a new wave of research on the determinants of political conflicts. Recent US humanitarian and peacekeeping involvements in Africa, the Carribean, and the Balkans are also fueling demands from government officials for research to help them better understand

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when and why nation-states are likely to collapse (Zartman, 1995; Epsey, et al, 1998). These efforts build upon earlier studies that were designed to identify the variables that correlate and can predict the onset of war (Small and Singer, 1982), the evolution of international crises (McClelland, 1976), and other forms of political instability (Rosenau, 1976). Many of the more recent research projects also rely upon past theoretical and empirical studies based on relative deprivation to predict when perceptions of resource disparity among less-advantage people are likely to induce the type of anger that triggers violent political conflicts (Gurr, 1985; Harff, 1992).

The evidence from older and more recent empirical studies regarding the role of environmental variables and inter-nation political conflict is mixed. Studies using a variety of research designs have not found evidence of strong, direct causal links among environmental variables, population growth, and political conflict. For example, case studies based on Homer-Dixon's theoretical framework found that resource scarcities acted as triggers to domestic political violence in situations such as South Africa and Rwanda only under certain conditions (Homer-Dixon and Blitt, 1998; Percival and Homer-Dixon, 1998). Recently, Homer-Dixon has argued more emphatically that it is hard to find clear historical or contemporary examples of major wars motivated mainly by scarcities of renewables such as crop land, forests, fish and fresh water (1999:11).

Global statistical studies of various types of nation-states conflicts tend to find that only a few variables are statistically significant predictors of inter-nation conflict. The most potent and statistically significant predictor variables are not environmental variables.

Past quantitative studies using event-interaction data to measure foreign policy conflict typically found that the most significantly predictors of nation-state conflicts were variables related to the geographic or demographic size of a nation-state, economic wealth, and the degree of a regime's political accountability (see for example Powell, et al, 1976).

Recent efforts to model domestic types of conflict have obtained similar results. The White House's State Failure Project, after examining the role of 75 predictor variables that had been identified by experts as being relevant for predicting state failure, found only three significant factors that discriminated between state failure and stable states. None of these factors were environmental ones. Instead, these factors were the level of material living standards (as measured by infant mortality); the level of trade openness; and the level of democracy. The second phase of this project, along with several other ongoing efforts are re-examining former relationships using new data and studying the impact of additional environmental variables.

More recent research based on updated and new data series is finding a similar pattern of mixed results. Several recent statistical studies have focused more narrowly on selective environmental resources such as the links between water quality, water scarcity, shared water sources and political conflict. Hauge and Ellingsen (1998) found a significant relationship between fresh water scarcity and increased levels of domestic violence, alone and in combination with land degradation and water availability. However, their correlation results also indicated that economic and political factors were the most potent predictor variables of political violence. In a study of shared water resources among nation-states, Wolleb, Toset and Gleditsch (1999) conclude that they could not determine whether the increased incidents of conflict between riparian states who share water resources were due to water scarcity or frictions over other water-related issues such as navigation, pollution, fishing.

Several works support the generalization that a narrow set of circumstances must be present in order for water issues to led to political conflict. Homer-Dixon (1999) emphasizes that upstream and downstream neighbors are only likely to go to war if the downstream country is highly dependent on the water for its national well-being; the upstream country is able and willing to restrict the river's flow; there is a history of antagonism between the two countries, and the downstream country is militarily stronger than the upstream country (Homer --Dixon, 1999: 13). In a similar vein, Swain (1997) and Wallensteen and Sollenberg (1998) provide evidence suggesting that incentives for cooperation are greater among riparian states when the issue is a qualitative rather than a quantitative problem of scarcity.

Mixed results have led many researchers interested in environmental variables as predictors of political conflict to call for more data and more refined data that can help researchers determine the nature of the issues causing political conflict. (Gleditsch, 1998; Wolleb, Toset and Gleditsch, 1999). There appears to be an emerging consensus on the value of data collected at the regional and sub-national level (Vayrynen, 1998). Other researchers are calling for new modes of analysis that can help us to understand how specific environmental issues develop within the broader context of economic

development, sustainability, conflict dynamics or regional security complexes (Buzan, et al; Wolleb, Toset and Gleditsch, 1999).

Unfortunately, few generalizations can be drawn from this literature. The comparability of these systematic studies is limited by the fact that different studies focused on different concepts or use different indicators to measure political conflict. This diversity of phenomena studied limits the extent to which comparisons can be made or knowledge can be accumulated and suggests the need for more research using similar concepts and indicators for independent and dependent variables. Interest and research in this area is likely to continue since many researchers and policy makers remain convinced that resource scarcity, environmental degradation, and population increases are likely to contribute to future political conflicts.

Why forecasting environmental-conflict linkages is difficult

There are several reasons why it is difficult to accurately predict when and how environmental events and trends will lead to political violence. One of the most famous examples of resource over-utilization leading to the collapse of human collectivities occurred on Easter Island (Kennedy, et al, 1998). Polynesian voyagers are believed to have arrived on a richly forested island around 400 ad. By the time Europeans arrived in 1722, Easter Island had descended into conflict and cannibalism (Kennedy, et al, 1998: 5).

This case is widely cited as a dramatic example of how deforestation and destruction of the environment led to the collapse of a civilization (see for example, Diamond, 1994). However, the collapse of civilization on Easter Island occurred over centuries rather than decades. This famous case suggests that the time frame required to make accurate long term forecast of when and how environmental processes will led to political violence or system collapse may be much longer than the one currently used to formulate and study public policy. This case also underscores the magnitude of the contemporary missing data problem and raises the possibility that existing modeling efforts may be unable to capture the complex, dynamic and long-term relationships among variables necessary to predict political instability.

The Easter Island case also illustrates the importance of an analyst's theoretical perspective and choice of variables. It may be the case that Easter Island is currently viewed as a clear cut example of environmental-political conflict linkages only because it is an ancient one. There may be too few interested living historians and researchers to have a lively debate over rival interpretations of significant causal variables.

This is certainly not the case today in environmental conflict studies where researchers using different and theories and research traditions are examining the linkages between environmental variables and political instabilities. For example, Homer-Dixon's case studies of environmental degradation and the onset of genocide in Rwanda focused on resource degradation and crowding in recent decades. In contrast, most African area specialists emphasize the need to understanding the effects of a variety of events and trends at least since the formal colonial period in order to understand how environmental degradation relates to political and economic changes in contemporary societies such as Rwanda (Prunier, 1995).

Many area specialists also place a great deal of explanatory weight on the effects of international and internal economic variables factors to explain the dynamics of modern environmental degradation (see for example, Gordon, 1996). More inter-disciplinary research may be useful as several recent studies by area specialists have documented how outside mandated pressures for economic and democratic reforms had the unintended consequence of fueling increased environmental degradation and sporadic bouts of political violence (see for example, Walker, 1999).

The importance of an analyst's perspective is dramatically underscored in a recent major review of research on the links between environmental quality and political conflict (Kennedy, et al, 1998). This study found that social scientists tend to conclude that economic and political rather than environmental factors are more important predictors of armed conflict. In contrast, researchers with a background in the environmental sciences tend to emphasize rates of environmental change, especially human-induced change, as the essential determinants of future relationships between environmental quality and conflict propensity (p. 8).

These discrepancies are not surprising given the complex and still poorly understood causal mechanisms linking environmental degradation, population change, and political instabilities. Furthermore, the possibility exists that both the nature and rate of change of key environmental processes may be changing and creating unprecedented

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interaction effects. As the world's population doubles over the next 50 years, the rate at which shared resources are consumed and various pollution processes interact may increasingly tax the carrying capacity of several inter-related economic systems in novel ways that are difficult to foresee at this point in time.

model the effects of multiple eco-systemic processes influences on social relationships and political stability is even greater. Thus, it is hardly surprising that efforts to model complex interactions among environmental variables and various types of political instabilities using classical statistical techniques have met with only limited success in generating accurate long-term forecasts.[2]

Forecasting ill-structured problems

At this point in our modeling efforts, it may be useful to supplement statistical modeling efforts with monitoring efforts based on past research on how humans solve different types of problems in other domains to better understand environmental-political conflict linkages. Psychologists who study problem-solving behavior make a distinction between structured and "ill-structured" problems. Structured problems have well-known boundary conditions and generally agreed upon optimal solutions. Ill-structured problems are more ambiguous types of problems with no agreed upon definition or boundary conditions.

There is a large degree of uncertainty associated with the outcomes of Ill-structured problems because this class of problems have no single, optimal solution (Voss, 1998). Focusing on how people solve ill-structured problems has been a productive strategy for identifying recurring patterns in the way political actors attempt to define, make decisions, and predictions about a wide range of political problems (see for example Sylvan and Voss, 1998).

This project used a problem-solving theoretical perspective to organize the components of a system to monitor "environmental security" issues in Africa because these problems fall within the rubric of ill-structured problems. Problem solving seems an

Current uncertainties about the timing, magnitude, or probability that global warming will generate specific types of second-order effects illustrates how difficult it is to model and make accurate long-range forecasts using existing data and forecasting techniques. The complexity involved in trying to

appropriate perspective because individuals typically state political queries as problems and then make judgments and predictions about specific political issues on the basis of an initial representation of the problem. Past research indicates that this initial mental representation affects all subsequent stages of political decision from how a problem is defined and accepted by relevant political actors through the structuring of solution paths and specific policy proposals (Snyder and Paige, 1958, Sylvan and Voss, 199Ɛ).

Since ill-structured problems have no single optimal solution, much of the preliminary stage of any decision making process involves building a consensus on a "shared problem representation" or definition of the problem. Research on how people actually make decisions suggest that even after agreement is reached on a shared definition of the problem, the process of reaching a decision or solution path is a messy process. This description of the political choice process differs markedly from the one assumed by rational choice models of politics. This is an important observation since relative choice assumptions underlie many contemporary methods of making political and economic forecasting efforts (Purkitt, 1991)

How an individual or group of political actors reach agreement on their initial problem representation of a specific public policy topic is also important for understanding how issues become part of the official public policy agenda (Kingdon, 1984). Understanding how collective representations of political problems develop is important because the solution path or specific policies that is adopted is usually embedded in the initial representation or way the problem is defined (Dyson and Purkitt, 1986, 1997; Sylvan and Haddad, 1998).

Research on how people attempt to solve political problems suggests that individuals rely heavily on prior beliefs, experiences and pre-existing policy preferences to interpret information and to structure a mental representation of a specific problems. Thus, ideology, scripts, images, and prior policy preferences rather than information typically determine how a specific political problem is defined or framed.

[2] It is surprising that more researchers studying the links between environmental variables and political conflict do not use dynamic modeling techniques, simulations, or insights gleaned from general systems theory (GST). For example, a basic proposition of GST is that the probability of system entropy and collapse increases as an open system (e g , the Southern African subsystem or the general international system) becomes more complex.

Once an initial representation is developed, it is highly resistant to change even in the face of contradictory information (Dyson and Purkitt, 1986, 1997; Carrol and Payne, 1976). This initial representation is necessarily a highly simplistic mental representation because of the space limitations of working memory.

Past research suggests that individual can only use 2-to-5 analytical dimensions systematically when they attempt to analyze or make predictions about ill-structured political problems (Purkitt, 1998). Instead, people use simplifying concepts and beliefs to construct an initial problem representation. This representation and the reliance on prior beliefs and value preferences rather than relevant incoming information often leads to analysts making normatively incorrect inferences and judgments (Plous, 1993). Psychologists have been cataloguing a rather large number of systematic and recurring cognitive biases (Hammond, Keeney, Raiffa, 1999). Unfortunately, the pervasiveness of cognitive conceit, or an unwarranted faith in the adequacy of our intuitive processes, leads most individuals to reject the need for explicit decision aids.

Identifying environmental security issues within a regional context

These insights about how individuals process information and develop a mental representation of ill-structured political problems guided the construction of a computer-based monitoring system of environmental problems that may create future political problems. Since it is important to understand how key political actors initially define issues, I first completed interviews with a diverse sample of experts who were knowledgeable about environmental and political issues in Southern Africa. In these interviews I avoided using the term "environmental security" since this is a complex and ambiguous term used primarily by US government officials and western-orientated researchers (Deudney, 1990; Levy, 1995; Foster and Siljeholm, 1998). Many policy makers, academicians and researchers in developing counties, as well as most of the public worldwide, are unfamiliar with the term.

To understand what types of issues individuals associate with the concept of "environmental security" in Southern Africa, I asked interviewees to "identify the most serious environmental problems facing their country and the region that they felt might lead to future political instability."

I conducted interviews with 64 experts working in the Untied States and six Southern African countries from 1996 through 1999. While care must be taken in making generalizations from a non-random sample, this group included knowledgeable and influential individuals who had extensive experiences dealing with political and environmental problems in Southern Africa. About half of the interviewees were government officials. The remaining sample members worked in senior positions for international or regional organizations, non-governmental organizations or held research positions in universities or policy institutes. The nationality of these interviewees included: US-11, South Africa- 35, other Southern African countries-15, other nationalities-3.

The most frequently mentioned environmental issue areas are listed in Table 1. A comprehensive list of the specific issues subsumed under these six issue-areas can be found in Purkitt (forthcoming, 1999).

Table 1 – Regional Environmental Security Issues or Threats

1. WATER SCARCITY
2. DEVELOPMENT-ENVIRONMENTAL ISSUES
3. NEED FOR REGIONAL MECHANISMS
4. PROTECTION AND MANAGEMENT OF RENEWABLE RESOURCES,
5. CROSS-BORDER FLOWS OF PEOPLE & GOODS
6. SOUTH AFRICAN AS THE REGIONAL HEGEMON

Top ranked issue areas identified as serious regional environmental concerns that might lead to future political conflict included: 1) Increasing water scarcity and how to manage shared river or water systems. This was considered the most serious environemental issue in the region because most rivers in Southern Africa are transnational; 2) A large number of developmental-environmental issues including behaviors generated by poverty, population growth, urbanization, industrialization, pollution, waste management, and climate changes; 3) Issues related to the limited capacity of national-states and regional organizations to cope with environmental problems requiring regional resources. This issue was often phrased as the the need for a stronger regional mechanism than existing resources and procedures available through the South African Development Consortium (SADC), the major international

organization in the region; 4) How to manage and protect renewable resources with issues related to wildlife and fisheries management being mentioned the most; 5) Cross-border flows of people, legal, and illegal goods and 6) South Africa as the regional hegemonic power. South Africa dominates this region and much of Africa economically and has the potential to be a military hegemonic power. A related theme was the idea that South Africa was both the creator and the key to addressing many regional environmental problems.

This list of issue areas has high face validity. Most analysts rank water scarcity as the most serious future environmental problem facing the region. Several countries in the region, including South Africa and Botswana, will be forced to rely on water resources located in poor countries in the northern portion of the region (i.e., Zambia and the Democratic Republic of the Congo) within a few decades in order to survive.

Namibia and Botswana nearly went to war in 1996 over conflicting territorial claims to a small island in the Chobe River. While this conflict over an island that is submerged for part of the year was turned over to the World Court for adjudication, it is only one of several water related issues causing tensions between these two neighbors. Since Namibia is a "dry country" that already lacks annual water resources to supply minimal annual water needs in the country, political conflicts between these two neighbors are likely to reemerge during the next drought period.

The emphasis on water scarcity issues and a host of interrelated development-environmental issues among members of this sample highlights the fact that what constitutes a "green issue" varies considerably across world regions. While some of the most serious environmental problems are concerns for most nation-states, other are not.

One example of a growing environmental problem that is shared by many former colonies is the problem of controlling alien vegetation. Several countries in Southern Africa face similar problems as spreading alien vegetation threaten to strangle critical water supplies. Alien vegetation is now classified as a "national security threat " in Zimbabwe. Since 1996, Zimbabwe military forces have participated in annual alien vegetation eradication programs (Interviews, July, 1997).

In South Africa, programs designed to eradicate alien vegetation are among the largest and most popular public works projects. South African water officials are convinced that such eradication programs are central to efforts to avoid conflicts with neighbors. At the height of the drought in the mid-1990s, when tensions between the two countries were running high, South African water officials claimed that eradication of vegetation eradication programs led to a 30 per cent increase in water flows to Mozambique. Several top South African politicians view eradication of alien vegetation as an important policy priority and means to prevent future conflicts with Mozambique. This is an important problem for both of these neighboring states. Each is now dedicated to achieving even more economic cooperation and integration in the future (Interviews, June, 1997).

A comparison of the major issue areas identified by participants in this study with those obtained from a global survey (N=31) indicates substantial overlap in terms of the general environmental issues, e.g., water, soil, deforestation, loss of biodiversity, food and migration (Millennium Project, 1997). However, several specific issues mentioned by interviewees in this study were not mentioned in the global survey.

Issues omitted in the global study were among the most important for participants in this study. These issues included development-environmental problems associated with poverty, population growth, and increasing rates of new and older diseases. The presence of both general and region-specific issues in this study's top mentioned environmental and population problems supports the recommendations of researchers who argue that more detailed data at the regional level are required in order to model how environmental and political problems and processes are related (Vavrynen, 1998; Hoftendorf, 1999).

Summarizing & comparing different "framings" of environmental-political issues

Most of the individuals interviewed for this study were also asked to "think aloud" about the probable implications of the specific environmental problems or issues they identified as ones likely to lead to future political problems. These think aloud-verbal protocols were recorded and coded using conventions developed by Ericsson and Simon (1984/1993), Bales (1950), and past experiments on political decision making (Dyson and Purkitt; 1986; Purkitt and Dyson, 1990). Using a problem solving approach to coding, pauses, hesitations, and changes in intonation are used to mark shifts in processing about a specific topic. These conventions permit coding of both the length and number of analytical topics or dimensions used by each interviewee. Free-hand cognitive maps or schematic diagrams can be used to summarize key

problem dimensions and links among objects developed by each interviewee (see Purkitt, 1998 for details)

These summaries of how individuals, or groups, represent a specific problems can be use for a variety of purposes. One use is to gain an explicit understanding of how different political actors frame the same policy issue. The mental representation or framing of several interviewees evidenced little structure. These problem representations approximated the simple "list-like" structure found among novices in other fields (see Purkitt, 1998 for a further discussion of this topic).

The first example in Figure 1 illustrates the simple, novice-like list structure of the problem representation developed by one "expert" in this sample. This interviewee started by singling out food security as the most serious environmental issue with political ramifications facing South Africa and the region. Although this representation had a simple structure, this framing contains useful information in an easy-to-understandable form about key actors and issues related to food security in the region. These schematic diagrams can also be used to explicitly compare alternative framings and policy solutions or to construct a more complete, composite "shared problem representation" of food security issues in the

Figure 1

Example 1: A List-like framing

Food Security

World Food Program dead

US Dept. of Agriculture not sensitive problems

African farmers (South Africa, Botswana)

South Africa

1-distribution of land
who owns, who will pay,
different organized actors by sector,

2-water

3-desertification

other issues related to agriculture

-Role of Banks
how to give people access to capital (BATA)

-Bioengineering of seeds

-Few are focusing on broader issue of food security

Example 2: Script-based approach

(Botswana is a conservative, developmental state, 75% live in rural areas

DIMENSION NO. 1 Symbiotic relations - traditional chiefs & government

CHIEFS **PARTY**

Support than in village" ruling party unpopular small god "above politics"...> civil servants work through Chiefs in rural areas

Ruling party also unpopular - urban youth

Political opposition parties dominate forums but young elite wants farms

DIMENSION NO. 2

Power flows through cattlemen - (very sensitive "beyond politics" 18 large owners).....>

key to understanding environmental issues

1-Water scarcity Okavampo pipeline-real threat of water scarcity sub-chief of Maun...> Presented to people as "issue that effects your life".....> real potential for conflict Botswana & Namibia

2-Disease fences Widely supported in Botswana.....>cows coming in with disease...>widely supported
....>Government responsive to 18 large cattle owners & indigenous herders & bourgeoisie all want cattle

Cattle are basis of wealth...>erection of fences

3-Environmental impact copper mining
...>little opposition (except Indians)

4-Lead role in SADO Secretariat in Gaborone
....>Botswana wants to will remain center trade, exchange & development

5-Bothswanan Defense Force **No. 1 government concern**
.....>"prevent coup".....>President's son wants to run for presidency
No fights since 1970s.....>no way to get promoted....>
....>Government supports a Botswanan role in regional peacekeeping

6-Military base Conservative regime terrified of ANC.....>
Botswanan government treated ANC poorly during struggle...>collaborated w SA police...>
.....>base started with Western support during apartheid era.....>

continued uneasiness with ANC government

region based on the inputs of many experts. Because these problem representation summaries are explicit and easy to understand, their construct validity can be judged by outside panels of experts.

The second schematic diagram in Figure 1 illustrates a more complex "script-based" representation of environmental problems in one country. This longer and more structured problem representation of environmental problems in Botswana was developed by an expert who first identified two fundamental dimensions of Botswana society that he felt were crucial for understanding environmental and political issues in Botswana. Next, this analyst identified six environmental issues. Most of these flow logically from the two-dimensional political script or mental representation of the problem. This script makes it easy for an observer to understood why certain issues, such as disease fences, are major environmental-political issues in Botswana. This explicit representation also makes it easy for the observer to see why different groups would frame the same issue differently. This representation may also help observers to better understand why Botswana is one of the most stable political systems in Africa.

The first dimension of this script pertains to the symbiotic relationship between traditional chiefs and a government that has been ruled by the same political party, the Botswana Democratic Party, since independence. The second dimension is a political power dimension. According to this analyst, political power in Botswana society flows from 18 large cattle owners who have a disproportionate ability to influence public policy. Since cattle is the basis of wealth and society in Botswana, the government can maintain high levels of legitimacy by promoting measures designed to ensure that young members of the elite will be able to amass cattle and by protecting the interests of cattlemen. This dimension of Botswana politics is a sensitive one, which is rarely discussed openly or in writing, as it raises the suggestion that political opposition parties and the formal democratic system in Botswana are largely symbolic features of the political system.

The richness of this protocol makes it a useful guide for constructing a future scenario of how environmental issues in Botswana might develop that could threatens the political stability of the existing status quo. The validity of elements of this scenario and the probability of future outcomes can be evaluated by different expert judges who are familiar with environmental and political issues in Botswana. This diagram can also be used as a point of departure for groups trying to forecast future political events or discuss future patterns of democracy in Botswana.

I used think aloud protocols, interviews with a senior official working on environmental issues for the Lesotho military, and published accounts of recent economic and political trends to construct a future conflict scenario. In this scenario, terrorists from Lesotho attack the water pipeline leading from the Lesotho Highland Dam Project to the Johannesburg Water district. This dam when completed will be the largest ever built in sub-Saharan Africa. It is already a major source of revenue for the Lesotho government. The first water from the dam started flowing into the Johannesburg Metropolitan Water District in 1998. Without this first shipment of water from the Lesotho dam, the greater metropolitan area of Johannesburg/Soweto would have experienced water shortages (Interview, July, 1997). Over time, water from the highlands of Lesotho will become an increasingly important source of water for the Johannesburg Water District.

My conflict scenario forecasts a future terrorist attack on this water pipeline in part because it will become an increasingly salient target for terrorists.

This scenario is also based on the long tradition of guerrilla forces in the region disrupting power supplies bombing hydroelectric dams. This scenario was also based on reports of declining support among citizens in Lesotho for a government that has been undergoing constant conflict between military and civilian leaders for years. This political crisis is occurring at a the same time that increased numbers of Basotho are experiencing difficulties finding jobs in South Africa.

This scenario was also based on information I obtained during a candid interview and "think aloud protocol" with a senior official who worked on environmental issues for the Lesotho military. This individual confirmed trends reported in more general sources and added personal details based on his work in local communities throughout Lesotho. He reported growing, but still muted, expressions of discontent among peasants in the highlands. According to this official, some chiefs in the highlands were attributing declines in crop yields to the use of fertilizers and hybrid seeds that the government had required peasants to plant in recent decades. While resentments were focused primarily towards the national government, this officers had also noticed increased signs of growing resentments directed at South Africa. These resentments are tied to the country's economic dependency on South Africa. As a mini enclave entirely surrounded by South Africa, most of the fertilizer and seeds used by these peasant farmers are imported from South Africa.

This officer was also noticing that resentments among urban residents, especially among young adults, directed at both their own government and South Africa, were increasing. Increased numbers of Basotho young men were returning home from South Africa after unsuccessful attempts to find jobs. Many of these youths had experienced hostility from South Africans as they looked for work and from South Africans in townships where they lived. Historically, Lesotho has served as a pool of cheap male laborers for South African mines and other industries while many Basotho women work for extended periods as cheap domestic workers. However, rising unemployment, aggravated by recent retrenchments in South Africa's mining sector, is fueling growing hostility towards foreigners in many of South Africa's poorer communities. This officer also reported hearing more complaints among urban areas residents of all social classes about industrial pollution from South Africa's industrial heartland that now routinely settles over Lesotho's formerly pristine skies.

Although none of these grievances were reported to be explicitly linked to the dam project, it is easy to imagine that future grievances may include complaints about the government's arrangement to sell precious water supplies to South Africa. If resentments increase among Basutos in the future, these grievances will increase at the same time that residents in the greater Johannesburg/Gueteng complex grow increasingly dependent upon water from the Lesotho Highland dam.

This scenario met with widespread skepticism in 1997 by South African and American defense analysts who heard it. This contingency was quickly dismissed as unrealistic given Lesotho's economic dependencies on South African financial resources and the extensive amount of inter-marriage among South Africans and Basotho. My scenario was also rejected because it contains several assumptions and projections that were not part of the conventional wisdom of mainstream strategic analysts.

However, the conventional wisdom that dismissed future political violence, including acts of political terrorism directed against South African targets, appeared less absurd after South African and Bostwana troops intervened militarily in Lesotho in 1998. This military intervention was intended to help the government put down a military mutiny. Initially, South African national defense forces planners viewed this first post-apartheid South African experience in international peacekeeping as a short-term and routine police action. However, there were extensive protests to the foreign invasion by citizens in both cities and rural areas in Lesotho.

SANDF troops were surprised by the extent of resistance and armed protests. The SANDF forces could not control the rioters in the capital for several days and much of the downtown commercial district was destroyed during these riots. There were also reports of sporadic armed protests in rural areas. South African and Botswana peacekeeping troops ended up extending their presence in the country from weeks to months (Smith, 1998, 1999). Most of this unrest was diffused rioting and looting which lacked an explicit political component such as grievances about the the Lesotho Highland Dam Project. However, my scenario seemed less implausible by the end of 1998.

This example illustrates how subjective data such as the information collected in these verbal protocols may be useful for identifying widely shared but potentially flawed assumptions and omissions among the conventional wisdom of policy experts. I was surprised by the extent of complacency among most

analysts in this region as they talked aloud about future water shortages in the region. Most shared an assumption that South Africa and her water parched neighbors would tap the watersheds of the Zambezi and Congo River and thus, avoid disruptions due to water scarcity in the future. However, none of these analysts made a connection between future water needs and ongoing political instability in the Great Lakes region. This omission occurred despite the fact that the Congo basin had already become a serious zones of instability by 1997 when these interviews were conducted. Despite these dramatic events, none of the analysts considered the implications of escalating political violence on efforts to deliver water supplies long distances from the Congo watersheds to countries in the south in the future.

A similar tendency to ignore critical aspects of an environmental policy area was also evident in discussions of illegal ocean fishing. While several analysts mentioned problems associated with illegal commercial driftnet fishing in the Atlantic Ocean, few analysts addressed what one interviewee characterized as the "rape of the Indian Ocean" (Interview, Maputo, Mozambique, July, 1997). This omission occurred despite published and word-of-mouth reports that suggested that more illegal fishing has shifted from the South Atlantic to the Indian Ocean in the aftermath of crackdown on illegal fishing vessels in many EC and Asian countries by 1997 (Interviews, Mozambique, July 1997; Washington D.C., March, 1999). Although the magnitude of illegal fishing in the Indian Ocean is unknown, the presence of modern drift-net factory ships working off the coast of Mozambique suggests that the extent of illegal fishing off Mozambique's coast is a serious problem. Yet none of these analysts addressed this problem.

These and several other omissions support the view that environmental problems that lack high visibility in the media, are not of direct and immediate concern to local or international elites, and problems whose future outcomes are cognitively difficult to imagine tend to be ignored until they reach catastrophic proportions. Unfortunately, conflicts tied to resource scarcity and the needs of increased numbers of poor people, that do not have obvious consequences for the wider region or world, are the types of environmental problems that are likely to grow more frequent throughout Africa in future decades.

Identifying and evaluating data sources

A final way that these in-depth interviews with individuals representing a diverse range of organization, environmental, and political interests proved useful was by helping to identify validity problems in specific statistical series and to locate relevant local sources of data.

Even in South Africa, where aggregate data series on many environmental variables have been collected for decades, these statistical series are of questionable validity. Senior officials in the Ministry of Water Affairs and Forestry acknowledged during candid interviews that one of the most serious problems facing this ministry during the post-apartheid era was how to get long-term employees who routinely manufactured statistical reports during the apartheid era to start sending in accurate data on key aspects of forest coverage and deforestation (Interview, June, 1997). This problem is a formidable one as these officials were not disciplined in the past for submitting false reports and can not be fired under existing personnel rules.

Despite the severe water problems facing South Africa, there was no systematic data on wetlands for the country until 1997. During my trip an environmentalist, who directed a local non-governmental organization concerns with the quality of wetlands in South Africa, had just obtained funding from the government to undertake the first nation-wide wetland survey. Since this individual heads a local environmental organization, it is doubtful that this data will be recorded in standardized African statistical references or used in future environmental security policy analyses.

I also found a wealth of data on water precipitation levels and other characteristics of water collected over this past 100 years in Namibia. These measurements are a major ongoing research activity of the Desertification Center of Namibia. However, there were no plans to make this data available to a larger audience (Interviews, July, 1997).

A final example of the type of rich data available from in-country sources are statistics on elephant poaching mortalities, poaching related firearms confiscated, and rhino poaching mortalities from 1980 through 1996. These data were collected by the chief warden in charge of security for Kruger National Park in South Africa. Although these statistics are limited to arrests inside Kruger Park, endangered species units of the South African police and national and provincial park officials in other areas of South Africa collect similar statistics for their areas of jurisdiction.

The trend in these statistics suggest that implementation of the Convention on Endangered Species (CITES) ban on ivory exports in the late 1980s did not have a major impact on elephant or rhino poaching inside Kruger National Park. Instead, a downward trend in elephant poaching and a concomitant increase in the flow of illegal firearms coincided with huge increases in cross-border illegal arms flows that occurred as the Mozambique civil war round down in the early 1990s. Kruger Park's chief warden felt that such data series were probably valid indicators of more general trends in cross-border illegal activities between the two countries.

One of the most important findings from the warden's data gathering efforts was support for the proposition that smugglers, whether they were animal poachers or arms smugglers, use the same basic paths through the park in their efforts to move illegal goods into and out of South Africa (Interview, July, 1997).

While no generalizations to other areas of South Africa or other countries involved in ivory exports can be made from these data, these data suggest that it is possible to compile a valid aggregate data series on wildlife poaching and illegal arms trafficking for South Africa. If similar statistics are compiled from the other three countries who received the right to renew exports of ivory in 1997, there would be adequate data for a quasi-experimental study of the effects that lifting the ban on ivory and other events had on elephant populations in these countries. These data would also be useful for tracking cross-border flows of small arms and other contraband. With the current emphasis on promoting eco-tourism as a means to promote jobs, sustainable development, and wildlife conservation, there is likely to be substantial interests in these data by several potential users.

Components of a multi-level monitoring system

Interview and data collected from local sources , along with updated schematic summaries of key actors and issues in the region, form components of a larger data base. A fully implemented monitoring system of environmental and political trends in Southern African region, other African regions, or other regions throughout the developing world could provide busy analysts, forecasters, and policy makers with relevant data needed to develop information-based problem representations. This information could also be used to periodically re-evaluate the adequacy of past framings of environmental problems and their links with specific public policies. Information in this system would need to be updated frequently to ensure that users had timely, valid, and reliable summary data. The amount of information should be kept to a minimum to ensure that analysts, forecasters, and policy makers would actually use it. To the extent possible, this system should be web-based and linked to a transparent email server and chat room open to interested individuals worldwide. While a public access list server would generate a lot of noise, it could also serve as the vehicle for timely and reliable feedback information from remote areas of the world. This system would also provide a central communication site that would permit researchers and practitioners to post notices and exchange views[3].

The proto-type system is organized around six environmental problem areas:

-Biodiversity
-Climate
-Desertification and deforestation
-Fresh water
-Oceans and fisheries
-Population trends

The format and type of information included under each of these problem areas is further classified under four levels of analysis: the global, regional, national, and sub-national level. A template with key prompts was designed to aid researchers in locating and summarizing information in a standard form. The key topics and types of data included under each of these

[3] The model for this email server and Internet chat room is ProMED. This email network, run by Health net, links more than 12,000 professionals working in health services and research within an electronic network This network allows professionals in the remotest parts of the world to communicate with colleagues in developed countries institutions such as the Center for Disease Control in Atlanta, US. (ProMED-mail promed@usa healthnet org) . Most ProMED users are interested in infectious diseases, chemical, biological, or nuclear induced illnesses, in addition to illnesses caused by other types of pollutants. This network and mode of communication is also an invaluable source of timely information about emerging environmental crises such as the recent crisis triggered by allegations that fishermen were using poison at night in Lake Victoria in increase their catch. Allegations of similar practices along the Nile River in Sudan were quickly discounted by observers on the spot in southern Sudan using the ProMED email service. For a further discussion of this case as an example of complex environmental crises that are likely to increase in the future, see Purkitt (1999).

topics are listed in Table 3. While I have not fully implemented this system, five undergraduates and I were able to compile preliminary data, expert judgments and summary analyses for each of these policy areas to illustrate the type of information to be contained in each problem area during one semester in 1998.

Each problem area is organized as a series of pages on a specialized Internet home page. Hyper links to relevant web sites, data sources, and other types of information, along with a brief bibliography of key books and recent articles for each level of analysis is also included. A partially implemented proto-type of this system is available online at:

http://members.tripod.com/~loose

Table 3 Format of Each Problem Area

GLOBAL

Overview The nature of the problem (i.e., magnitude and scope of problems)

Implications - "What if" this problem is not addressed? What will happen? When? Why?

What is the current and future probability that these environmental problem will worsen or spill-over to other areas?

What is the probability that this problems will led to political conflict or violence at the international level?

REGIONAL -same format except the focus on the nature and magnitude of the problem, relevant research, current responses, policy recommendations, key problems and constraints, implications and probability estimates are made at the regional level

NATIONAL - same format with a focus on problems research, responses, recommendations, key problems and constraints, implications, and probability estimates focused at the national level

SUB-NATIONAL - same format with a focus on problems at the sub-national level that might escalate in the future

Dimensions of each problem
including schematic diagrams of relevant problem representations

Summary of most recent scientific research
including: what's known about the problem
points of contention
relevant data sources
future research needs

Current international responses
(i.e., by UN, World Court, NGO, governments & status of relevant conventions & treaties

Most common (& novel) policy recommendations
(i.e., by whom, estimates of feasible, and possible funding sources)

Key problems and constraints
including estimates of which problems can be addressed at this level and possible funding sources

Saliency of each issue at the international level?

While the jury is still out on the usefulness of such a system, feedback from students and my colleagues in the US and Africa has been positive. One of the unanticipated uses of a web-based system was to make a large amount of information published in the west available to African students and researchers who often do not have easy access to updated textbook or academic journals.

A second unexpected conclusion from this study is that I found that the concept of "environmental security" is a useful analytical construct. Although the term is ambiguous, its novelty forces an analyst to consult a more diverse range of sources and to think about the implications of political and environmental problems not normally used in national security policy analyses. This is because an analyst must address a number of novel questions including: assessing the nature, magnitude and possibility of interactive effects of specific environmental problems, the effectiveness and priorities of key international organizations, non-governmental organizations, and nation-states, who are the critical actors at all levels of society. The environmental security construct also requires an analyst to consider how well the political system is coping and planning to cope with specific environmental issues in the immediate, medium, and long-term future? Thus, an analyst must think well outside his or her conventional inteliectual framework or "box". The exercise of developing and maintaining such a system may also be a productive way to

encourage analysts, forecasters, and policy makers to reexamine their assumptions and beliefs as they develop new problem representations about future possible environmental-political problems.

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The Ten 'Suggestions' on How to Teach Forecasting to Adults: What Your Parents Should Have Told You About Teaching Adults

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This paper is a summary of remarks made during a panel discussion "Issues in Teaching Forecasting: Applied Forecasting" at the **Nineteenth International Symposium on Forecasting** on June 28, 1999.

In teaching forecasting to adults with BA's in areas unrelated to forecasting, I discovered how not to teach forecasting. The typical USDA Graduate School class is 10 weeks with class meetings one night a week for three hours. This teaching context requires different strategies than teaching lengthy undergraduate or graduate courses in a two-semester sequence. I developed a set of rules for teaching a first forecasting course to adults in an evening school environment. I learned these by violating them egregiously in teaching a course on applied forecasting.

1. KEEP IT SOPHISTICATEDLY SIMPLE (KISS)

Keep the course sophisticatedly simple. KISS means straightforward, relevant, interesting, and insightful in the context of your customers. Give the students a good start in forecasting--do not give the impression that there is a foolproof strategy which will fit every forecasting problem. It is better to cover the basics well, and give students general insights so they can pick up specific techniques later. Teach one or two smoothing techniques, motivate their role, guide students in using live data and leave the more sophisticated techniques for a later course. The course is an introduction where elementary concepts are presented.

2. CHOOSE THE MOST RELEVANT OF THE BASIC MATERIAL

A corollary of keeping a course simple is to cover a reasonable amount of material. Choose the most useful topics and stress those with repetition in different contexts. Do not try to teach too many simple, but when massed together unconnected ideas. There is enough confusion as beginners learn basic skills. My attempt to be comprehensive in a ten-week course was a failure. I finished with only three students. One was a PhD in agricultural economics and the other two had extensive backgrounds in applied forecasting. Preaching to the choir is poor music and bad homiletics.

3. KEEP HOMEWORK ASSIGNMENTS SHORT, SELECTIVE, AND DOABLE

A corollary of relevant selectivity is giving a reasonable amount of homework and reviewing it in the next class after it was handed in. If a problem set is too long for you to correct it in one week, it is too long to assign. The opportunity to provide good feedback in a ten-week course is limited by delayed homework return. The duo of assigning well-chosen homework and getting it back quickly are important teaching tactics in a technical course.

4. FOCUS ON FORECASTING--REQUIRE STATISTICS AS A PREREQUISITE

A forecasting course should have a basic statistics course as a minimal background, with some background in regression analysis desirable. Learning basic statistical principles is time consuming and challenging enough in itself. The attempt to develop statistics background and the forecasting techniques crowded out the most important teaching tactic–lots of hands on training. Time spent on teaching basic statistical ideas makes for less time to teach students about forecasting.

5. HANDS ON IS BEST FOR MOST STUDENTS

The most important in-class learning tool is hands-on use of Eviews or another high level time series package. Several of the students who dropped the course saw the sessions on the computer using Eviews as the most valuable part of the course. Those who finished also found the Eviews practice sessions useful. But the relative time spent in hands on exercises was too small to extract maximum benefit from in class practice. High quality assisted practice makes good basketball players and good forecasters.

6. MURPHY'S LAWS OF SOFTWARE AND HARDWARE PREVAILS

Despite requesting a room of computers for the course, my first assigned room had no computers. The next week many of the disks for the student versions of Eviews were defective. One week was lost due to lack of hardware, another because of software failure. The moral: inspect the room to make sure that you have working computers or call ahead a few days in advance to check on computer facilities. Second, bring your own student version of the class software to class so students can install yours temporarily. Forecast the worst scenario, assume it, and take prudent precautions to ameliorate Murphy's nefarious laws.

7. USE MACROECONOMIC AND FINANCIAL DATA FOR EXAMPLES

Energy and agricultural data were too arcane for many students. Adult learners in the Washington, D.C. area know quite a bit about basic economic institutions and most read the newspaper. Almost all of your students know who the Federal Reserve chairman is and what the prime rate is, even if they do not know what the prime is on a particular day. Failing to use macroeconomic and financial data more extensively made some students lose interest. (As a Macroeconomist, I have a natural bias here.)

8. MAXIMIZE THE PROBABILITY OF FORECASTING PROJECTS BEING COMPLETED

For a skill building course, a take home project is an absolute necessity. Giving students too much time to choose a project caused some students to drop out of the course. The usual bind of having no topic caused otherwise capable students to drop out. Of course, it is best for students to pick their own topics but many do not have clear project ideas. So, have a sufficient number of data sets ready in usable data formats for projects. Further, most adult students do their best in working in teams–make the teams up if they are not naturally chosen. Finally, get a preliminary look at all the projects (rough draft) so you can prevent students going off in a wrong direction. Successful project completion takes planning and diligence on the instructor's part.

9. FOLLOW THE BOOK

In any introductory course, straying far from the text makes many students unnecessarily uncomfortable. I handed out supplementary material from several web sites. Some of the supplementary material used different notation than the text and caused a great deal of confusion. Different examples, particularly if they are gone over as hands on in class exercises, are helpful. The question is: Does supplementary material clarify the text/lecture concepts in the text or does it increase the material covered? Clarification and amplification are desirable, backdoor piling on of concepts is usually undesirable.

10. STRESS THE IMPORTANCE OF PUTTING A FORECAST IN CONTEXT

Besides standard textbook forecast evaluation criteria, there are also informal ones. Forecasts are typically done for an organization, and forecasts need to be useful in that context. A highly accurate forecast is useless if not needed. The best technical forecast of a variable not related to organizational needs at least indirectly may be less valuable than a technically poor forecast serving some organizational need. Few forecasts are purely academic exercises as real money and decisions are often influenced by forecasts. Students need to be reminded about forecast context issues.

A PRELIMINARY EVALUATION OF USDA'S EXPORT FORECASTS

Stephen MacDonald, Economic Research Service

USDA's forecasts of annual U.S. crop production, consumption, and trade are the acknowledged benchmarks for forecasters and market participants around the world. Beginning in the fall of each year, the level of crop production across the Northern Hemisphere is already largely realized for that year, and much of the remaining uncertainty for the United States concerns crop use. Exports are much more variable than domestic consumption, driving the post-harvest price variability that in part determines changes in farm income and subsequent production levels.

Extreme export variability during the early 1970's led USDA to establish a system for developing and publishing forecasts that is still in place today. The publication of USDA's forecasts is overseen by its World Agricultural Outlook Board (WAOB). WAOB members chair Interagency Commodity Estimates Committees (ICECs) for wheat, coarse grains, rice, cotton, oilseeds, meat animals, dairy, poultry, and sugar. Representatives for other USDA agencies are also ICEC members, including the Economic Research Service (ERS), the Foreign Agricultural Service (FAS), and the Farm Service Agency (FSA). The published forecasts are derived through a Delphic process in which each agency presents varying combinations of quantitative and judgmental analysis of current and future market conditions.

Each quarter, USDA publishes the *Outlook for U.S. Agricultural Trade* with forecasts of annual export value and volume for U.S. agriculture in total and by a number of specific crops and aggregates of crops. These forecasts are based on the process desribed above. The first forecast for each fiscal year (October-September) was published in November during most of the period studied. Revised forecasts are then published in February, May, and August. The first forecast studied for each year is determined after the previous year's actual realization is known, eliminating the complication that overlapping forecasts can introduce into testing forecast efficiency.

This study presents some preliminary characterizations of USDA's forecasts of annual fiscal year export levels for a number of agricultural products published the *Outlook for U.S. Agricultural Trade* during fiscal years 1977-98. The presence of unit roots in many of the forecast series and the series of their respective actual realizations highlights the need for further research using techniques such as cointegration to verify some of the rejections of forecast efficiency. The forecasts exhibit varying degrees of efficiency, bias, and accuracy, with only a relatively small subset exhibiting either bias, relatively low accuracy, or inefficiency. The aggregate agricultural export forecast exhibits high accuracy and an absence of bias, as do the forecasts for the major grain crops, wheat and corn.

Overview

A numerical forecast (F) of a variable is the expected future value of the variable's actual realization (A). In retrospect, a series of such forecasts in different time periods can be analyzed to characterize the performance of the forecasting individual or institution. Each time period's forecast is likely to differ from that period's actual realization with some degree of error, and the nature of this error provides a basis for the forecast's evaluation. If the error (E) is always zero, the forecast is perfect. If $E > 0$ or $E < 0$ in every case, the forecast is clearly biased. If the forecast has a more complicated relationship with the actual realization, but consistently maintains that relationship, it may be considered inefficient, or may fall under a broader definition of bias. Finally, the relationship between F and A can appear to be random, a result which probably defies the intent behind producing the forecast.

Since generally forecasts are neither perfectly accurate nor largely random, a common approach to forecast evaluation is to study their efficiency. The study of the rationality or efficiency of forecasts bears a great deal of similarity to much of the extensive efforts to test the efficiency of markets (see Fama (1991) for a survey). In agricultural economics, market efficiency has been most widely studied in the context of the ability of futures markets to predict spot prices. Garcia, et al (1988) survey this topic, which remains an object of inquiry (e.g. Kastens and Schroeder, 1996). The rationality of economic agents and their expectations has also been studied, but often with a set of techniques quite distinct from those used in market and forecast efficiency analysis.

One important difference between market and forecast efficiency analysis is that the core test of forecast rationality, described below, when applied to the market

efficiency hypothesis, becomes a joint test of the market's efficiency and the nature of its associated asset pricing model. An important aspect of the market efficiency literature includes examination of appropriate asset pricing models, risk premia, and the optimal degree of efficiency. These considerations are generally not applicable to evaluations of the rationality or efficiency of forecasts.

Other useful approaches to forecast evaluation include manipulations of the average of forecast error beyond the simple average used to illustrate bias. Simple errors can be manipulated into standard errors, root mean squared errors (RMSE), and mean absolute errors (MAPE) to name a few (see Mathews and Diamantopoulos (1994) and Armstrong and Collopy (1990) for details). Comparison of a series of forecasts and realizations can also be used to determine forecasters' ability to anticipate turning points, or the accuracy of forecasts in terms of direction of change (e.g. Schnader and Stekler, 1990).

In this study, USDA's forecasts of annual agricultural exports are evaluated. The forecasts include value and volume for a number of crops and aggregates of crops, and the value of total agricultural exports by geographic destination. The value forecasts evaluated include: Total agriculture, Grains and feeds, Wheat and flour, Rice, Coarse grains, Oilseeds and products, Soybeans, Soybean cake and meal, Soybean oil, Livestock products, Poultry and products, Dairy products, Horticultural products, Tobacco, Cotton and linters, Sugar and tropical products, and Seeds. The evaluated volume forecasts are: Wheat and flour, Coarse grains, Rice, Soybeans, Soybean cake and flour, Animal fats, and Cotton and linters. The geographic destinations are: Western Europe, Eastern Europe, the USSR, Japan, China, Other Asia, the Middle East, North Africa, Sub-Saharan Africa, Latin America, Canada, and Oceania.

The next section describes the efficiency and accuracy measures applied to these forecasts, followed by a description of the results of calculating these measures, and some possible explanations for some of these results.

Methodology

The core test of forecast rationality or efficiency--developed by Theil (1958)--is based on testing the estimated parameters of the following relationship between the actual realization of the forecasted variable (A) and the forecast of that variable (F):

$$A = \alpha + \beta F + \epsilon$$

The parameters serve to characterize the linear relationship between F and A where ϵ is the random error term, while α and β are parameteres to be estimated. If $\alpha = 0$ and $\beta = 1$, then the forecast is considered unbiased or efficient. An analogous approach is often applied for futures market efficiency by substituting a spot price (S) for A, and a futures price (F) of the same good for F. In addition to this efficiency, the absence of serial correlation in the error term is often considered necessary to meet the standard variously described as rationality or "weak-form" efficiency (the term efficiency will be used throughout the rest of this paper). An additional criteria for a "strong-form" level of efficiency is that the forecast embodies all available information.

Efficiency tests are only one part of the evaluation of a forecast. The simultaneous $\alpha = 0$ and $\beta = 1$ test or the test solely of $\beta = 1$ can fail either: 1) because the forecast is highly inaccurate, thus β cannot be distinguished from zero, or 2) because the forecast is largely equivalent to a linear transformation of the actual realization, thus, β could be distinguished from both 0 and 1. While both such forecasts are inefficient, the second is almost certainly more accurate. Accuracy measures--such as root mean squared error (RMSE), mean absolute percent error (MAPE), or correlation--combined with an examination of systematic linear error together provide insights into a forecast in several useful dimensions. Only one accuracy measure--correlation--is presented here, while no strong-form efficiency tests are applied.

Following Granger and Newbold (1986) the forecasts are tested as differences from the actual values of the previous year. Even in differenced form, nearly all the variables examined are nonstationary, possibly due to the cycles exhibited by agricultural exports during the period studied. Parameter values for each pair of series were estimated using ordinary least squares (OLS). The Durbin-Watson statistics were calculated in each case as a measure of serial correlation, and an F-test was performed for $\alpha = 0$ and $\beta = 1$ simultaneously. While inference based on OLS can lead to inappropriate rejection of efficiency, the accuracy and simple bias measures also computed to reinforce the rejection of efficiency in a number of cases. Cointegration analysis would have arrived at different conclusions for only a subset of the forecasts where efficiency is rejected.

Since the coefficient of determination (R^2) of a single

variable regression is equivalent to the square of the correlation between the dependent and independent variables, and the R^2 is part of the standard regression output, R^2 is used to capture the correlation.

Similarly, the simple bias of each forecast is tested by manipulating the equation used to test efficiency. The value of α is estimated when the value of β is restricted to 1, giving:

$$A - F = \alpha + \epsilon$$

and if $\alpha > 0$ or $\alpha < 0$, then the forecast suffers from simple bias. The failure of the simultaneous test for $\alpha = 0$ and $\beta = 1$ is often referred to as bias in the literature, but that term is reserved here for an average forecast error different from zero. The results of this test are essentially the same as those from a matched-pair test. The forecast bias table presented in the next section reports the values of F - A rather than A - F for interpretive convenience, since then the reported values represent how the forecast differs from the actual realization on average. When there is no significant difference, no value is reported in Table 4, a convention followed in all the tables. Every variable is forecasted in every quarter.

Results

The correlation results indicate the relative accuracy of USDA's forecasting efforts across time, crops, and regions. The earliest forecasts are virtually always the least correlated with the actual realizations. When the latest forecasts are published, the year is almost over, and the forecasts and actual realizations are highly correlated (Tables 1-3).

Across commodities, the most highly correlated value forecasts are those for grains, cotton, and soybean oil (Table 1). On the one hand, this may seem to reflect the intelligence gathering and analytical priorities of USDA, since government programs are important for each of these crops. Note that the correlation for soybeans in the earliest forecast is only 20 percent, one-half to one-third the correlation of wheat, corn, and cotton.

Alternatively, the range of correlations from 7 and 15 percent for livestock and horticultural products, respectively, to 55 and 66 percent for cotton value and wheat value, respectively, may capture the different role international trade plays in the consumption of these sets of commodities. Cotton and the grains exported by the United States are largely produced in the Northern Hemisphere, and are relatively undifferentiated with respect to place of origin. Importers are accustomed to adjusting the level of trade in response to their own production, and are usually shifting among sources of trade in response to varying production levels among exporters. Northern Hemisphere production shortfalls for a given crop year are largely discernable even as early as when the earliest forecasts for a given year examined in this study are published, giving insight into demand by potential importers and competition from potential exporters. On the other hand, differentiated, high-value products (HVP) like fruits and meat undergo such fluctuations to a much smaller degree. Rapid substitution and weather-driven shortfalls play a much smaller role in determining the level of exports, depriving these forecasts of the insights that market intelligence brings to predicting fluctuations in bulk crop exports.

The intermediate correlation of the soybean value forecasts supports this theory. The most prominent competitors for U.S. soybeans in world markets are two Southern Hemisphere countries, Brazil and Argentina. When the U.S. November forecast is published, the magnitude of competitor production is unknown, making export volume and prices difficult to forecast. By the time the February forecast is published, Southern Hemisphere planting weather and intentions are largely clear, and the correlation of the soybean value forecast rises dramatically, to 71 percent, while horticultural and livestock are still languishing at 42 and 8 percent, respectively.

Table 2 shows the crop volume forecast correlations, which are much higher in the earlier soybean forecasts than are the soybean value forecast correlations. This suggests that the forecast errors lowering the November soybean value correlation may be errors more in forecasting export price than in export volume. Table 3, on regional forecasts, highlights the difficulty USDA has in producing highly correlated forecasts for HVP's, with the lowest early season correlations realized for the markets with some of the largest HVP commodity-composition shares: Western Europe, Canada, and Oceania.

Table 4, forecast bias, indicates the possibility of some linear forecast errors, but also highlighted the need for further examination. Cotton provides examples of both, with the November cotton volume forecasts apparently averaging about 100,000 tons below each year's actual exports. Originally, a similar degree of bias in the

opposite direction was found for the final forecast of the year, however, regressing the fiscal year forecasts against adjusted marketing year data from USDA's database (Economic Research Service, 1998) did not show this bias. The original estimate had used U.S. Bureau of Census data to determine the actual realization, since this was the historical realization published in the *Outlook*.

However, during 1977-98 USDA's Interagency Commodity Estimates Committee (ICEC) for cotton determined that Bureau of Census data had undercounted exports in two years, and in those two years the ICEC had deviated from the usual practice of equating cotton exports in the USDA database with the exports reported by the Bureau of Census. Without this insight into the forecast methodology of the ICEC one would have little choice but to believe the late season cotton forecasts were inefficient and suffered from upwards simple bias.

A handful of other commodity forecasts also appeared to suffer from simple bias--downwards in every case--and it remains to be seen whether data issues analogous to those for cotton are only creating the appearance of bias. For example, discussions with members of the ICEC for rice suggest that the rice forecast may be calculated on a milled-basis, and that the appearance of bias may follow from comparison with a realization calculated on a product-weight basis.

Recent research (Bailey and Brorsen, 1998) has also found bias in some USDA commodity forecasts, and this bias was confined to the earlier portion of the 1982-96 time period. A casual examination of the distribution of bias across 1977-98 of the forecasts in this study does not support this notion, but a more rigorous examination would be an appropriate subject of further research.

A few of the regional forecasts also exhibit bias, but the regional forecasts are not a central focus of the process behind the *Outlook*, and changes in the definitions of aggregates (e.g. East Germany leaving Eastern Europe, expansion of the European Union) and revised data collection procedures for trade with Canada may have played a role in the apparent bias reported in Table 4. Regarding regional accuracy: accuracy remains relatively poor for exports to North Africa and to the Middle East through the latest forecasts of the year (Table 3). Intense competition with the European Union for these adjacent markets may account for this performance. Early season inaccuracy in forecasting exports to Western Europe and Canada may be due to important role soybeans play in exports to Western Europe and the importance of horticultural exports to both markets.

The rejections of forecast efficiency (Tables 8-10) in some cases can be traced to inaccuracy, e.g. forecasted exports to Western Europe and Canada have low correlation in November, and fail the efficiency test. Other rejections appear to relate to bias, e.g. rice and soybean meal volume. Since both findings of bias should be considered preliminary pending archival research to rule out the possibility that changes in tariff code definitions or similar problems caused the appearance of bias, the finding of inefficiency should be considered preliminary as well.

The rejection of efficiency for coarse grains value and total export value have weaker corroboration. In each case the estimated value of $\beta > 1$, which could indicate underestimation of the amount of change. The presence of positive serial error correlation (Tables 5-7) for these and a number of other forecasts suggests a persistent lag in discerning multi-year cycles and trends in exports. Interestingly, the rice volume forecast errors (Table 6) exhibit negative serial correlation, as do the actual realizations for total world and U.S. rice exports for much of the period studied. Again, this would be consistent with an underestimate of change, and the estimated value of $\beta > 1$.

This presence of unit roots reduces the reliability of the standard statistical tests on parameter values as undertaken in this study. This suggests that in some of cases where A forecast fails the efficiency test, the forecast may in fact be efficient. As noted earlier, in A number of cases the efficiency failure can be corroborated through other evaluation measures, but for A subset of forecasts, uncertainty remains. Further research is necessary to see if this subset of results in this study match the results supported by cointegration analysis.

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Table 1--Correlation of forecast change with actual change in value, by commodity and quarter, 1977-98[1]: Regression coefficient of determination (R^2)

Commodity	Nov.	Feb.	May	Aug.
		Percent		
Grains and feeds	59	85	94	98
Wheat and flour	66	83	93	98
Rice	54	50	80	93
Coarse grains	47	91	93	99
Oilseeds and products	8	54	82	96
Soybeans	20	71	83	96
Soybean cake and meal	30	80	81	92
Soybean oil	75	82	92	95
Livestock products	7	8	34	74
Poultry and products	0	33	61	92
Dairy products	1	17	51	77
Horticultural products	15	42	81	87
Tobacco	30	43	48	71
Cotton and linters	55	86	95	97
Sugar and tropical products	24	58	81	87
Seeds	13	7	10	12
Total	33	67	93	98

[1]Some value forecasts were made only during 1981-98: Wheat and flour, coarse grains, rice, soybeans, soybean meal, and soybean oil.

Table 2--Correlation of forecast change with actual change in volume by commodity and quarter, 1977-98: Regression coefficient of determination (R^2)

Commodity	Nov.	Feb.	May	Aug.
		Percent		
Wheat and flour	55	75	87	95
Coarse grains	41	78	90	98
Rice	59	77	77	95
Soybeans	72	81	90	98
Soybean cake and meal	60	72	81	96
Animal fats	28	1	55	82
Cotton and linters	71	86	95	98

Table 3--Correlation of forecast change with actual change, by region and quarter,1977-98: Regression coefficient of determination (R^2)

Commodity	Nov.	Feb.	May	Aug.
		Percent		
Western Europe	5	46	92	96
Eastern Europe	46	84	90	96
Former USSR	34	86	92	98
Japan	45	73	89	94
China	29	59	88	97
Other Asia	23	80	90	96
Middle East	14	23	39	77
North Africa	38	68	67	84
Sub-Saharan Africa	58	66	81	94
Latin America	38	59	81	96
Canada	9	18	82	93
Oceania	1	21	75	77
Developed countries	15	52	89	96
Less developed countries	28	68	87	96
Centrally planned countries	52	83	94	98

Table 4--Forecast bias, by quarterly forecast, 1977-98[1]

Commodity and region	Nov.	Feb.	May	Aug.
		1,000 metric tons		
Commodity:				
Rice	-78 (2.012)*	-161 (2.421)**	-156 (2.687)***	-120 (4.209)***
Soymeal	-340 (2.449)**	-264 (2.506)**	-89 (2.284)**	--
Cotton	-107 (2.170)**	--	--	--
		Million dollars		
Oilseeds	--	--	--	-101 (2.076)**
Horticultural	-144 (1.717)*	-179 (2.114)**	--	--
Region:				
Eastern Europe	103 (1.764)*	62 (1.732)*	68 (2.450)**	30 (1.803)*
Other Asia	--	--	--	98 (1.986)*
Middle East	--	--	129 (2.117)*	44 (2.226)*
Latin America	-362 (2.298)**	-308 (2.393)*	-226 (2.598)**	-112 (2.752)***
Subsaharan Africa	--	--	--	-36 (2.647)**
Oceania	--	-25 (2.279)**	--	--
Canada	-191 (2.424)**	-154 (2.071)**	-82 (2.309)**	-41 (1.808)*
Centrally planned countries	--	--	--	102 (2.708)***

[1]T-statistics for difference from zero in parentheses:
* = significant at 10 percent
** = significant at 5 percent
*** = significant at 1 percent.

Table 5--Serial correlation of value forecast errors, by commodity and quarter, 1977-98[1]: Results of Durbin-Watson test

Commodity	Nov.	Feb.	May	Aug.
		Durbin-Watson		
Grains and feeds	1.04	--	--	--
Wheat and flour	ind.[2]	--	--	--
Rice	--	--	ind.[3]	ind.[3]
Coarse grains	ind.	--	ind.	--
Oilseeds and products	--	--	--	--
Soybean cake and meal	1.08	0.80	0.76	ind.
Soybean oil	--	--	--	ind.[3]
Poultry and products	0.76	1.24	--	--
Horticultural products	--	ind.	ind.	--
Tobacco	--	--	--	ind.[3]
Sugar and tropical products	--	ind.	--	--
Total	1.16	--	--	--

[1]Some value forecasts were made only during 1981-98: Wheat and flour, coarse grains, rice, soybeans, soybean meal, and soybean oil.
[2]Indeterminate at 5% significance.
[3]Indeterminate with respect to negative correlation.

Table 6--Serial correlation of volume forecast errors, by commodity and quarter, 1977-98: Results of Durbin-Watson test

Commodity	Nov.	Feb.	May	Aug.
		Durbin-Watson		
Coarse grains	ind.[1]	--	.88	--
Rice	2.96	--	--	--
Soybean cake and meal	--	ind.	ind.	ind.
Cotton and linters	--	--	--	ind.

[1]Indeterminate at 5% significance.

Table 7--Serial correlation of value forecast errors, by region and quarter, 1977-98: Results of Durbin-Watson test

Commodity	Nov.	Feb.	May	Aug.
		Durbin-Watson		
Western Europe	--	--	--	2.89
Eastern Europe	ind.[1]	--	--	ind.
Japan	1.17	--	--	--
Other Asia	ind.	--	--	ind.
Sub-Saharan Africa	ind.	--	--	--
Latin America	ind.	ind.	--	--
Oceania	--	--	ind.	--
Developed countries	ind.	--	--	2.82
Less developed countries	ind.	--	--	--

[1]Indeterminate at 5% significance.

Table 8--Weak-form efficiency test for value forecasts[1], $\alpha=0$ and $\beta=1$

Commodity	Nov.	Feb.	May	Aug.
		F-statistic		
Coarse grains	--	5.76***	--	--
Oilseeds and products	2.70*	--	--	--
Soybean cake and meal	3.28*	3.45*	2.87*	--
Soybean oil	3.49*	2.65*	--	--
Livestock products	9.83***	3.58**	--	--
Poultry and products	2.98*	--	--	--
Dairy products	4.74**	--	--	--
Total	--	--	3.51**	--

[1]Some value forecasts were made only during 1981-98: Wheat and flour, coarse grains, rice, soybeans, soybean meal, and soybean oil.

* = significant at 10 percent
** = significant at 5 percent
*** = significant at 1 percent.

Table 9--Weak-form efficiency test for volume forecasts, $\alpha=0$ and $\beta=1$

Commodity	Nov.	Feb.	May	Aug.
		F-statistic		
Rice	3.76**	8.93***	5.76***	15.78***
Soybean cake and meal	2.88*	3.22*	2.54*	--
Animal fats	19.77***	5.87***	--	--

* = significant at 10 percent
** = significant at 5 percent
*** = significant at 1 percent.

Table 10--Weak-form efficiency test for value forecasts, $\alpha=0$ and $\beta=1$

Commodity	Nov.	Feb.	May	Aug.
		F-statistic		
Western Europe	3.30*	--	2.78*	--
Eastern Europe	--	4.82**	3.25*	--
Middle East	4.38**	--	--	--
North Africa	--	--	4.52**	3.90**
Sub-Saharan Africa	2.66*	--	--	5.34***
Latin America	3.32*	--	3.97**	4.15**
Canada	2.68*	--	3.03*	--
Oceania	30.92***	13.70***	42.36***	41.10***
Developed countries	--	--	4.23**	--
Less developed countries	--	--	--	--
Centrally planned countries	--	--	3.35*	4.59**

* = significant at 10 percent
** = significant at 5 percent
*** = significant at 1 percent.

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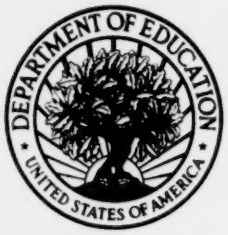

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